How to Evaluate an Early-Warning System: Toward a Unified Statistical Framework for Assessing Financial Crises Forecasting Methods

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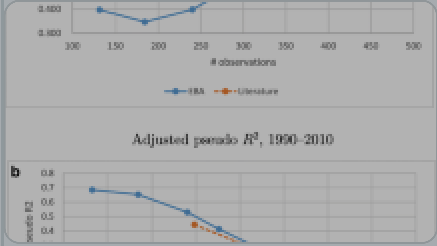
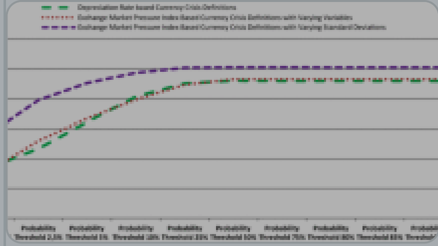
predicting currency crises exclusively for South-Asian countries. Besides, the optimal cut-off correctly allows us to identify now on average more than 2/3 of the crisis and calm periods.





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Notes

1. We do not tackle here the pertinence of the crisis dating. We assume that

5. Also called Correct Classification Frontier, as in Jorda, Moritz, and Taylor (2011).

6. This nonparametric estimator of the AUC criterion has recently been considered by Jorda, Moritz, and Taylor (2011) in the EWS literature, so as to compare different specifications with the random model (AUC=0.5).

7. Contrary to Jorda, Moritz, and Taylor (2011), who rely on a graphical comparison of the AUC for different models, we develop a statistical framework to evaluate EWS.

8. Let us assume that model 1 is the parsimonious model and model 2 is the

12. The results for the other countries are available on request.

13. In the case of KLR the threshold equals three standard deviations; however, in this case, Taiwan would never register any currency crises, which is historically not accurate. For example, Taiwan was not exempted from the Asian crisis in 1997.

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Electronic supplementary material

Supplementary Tables

Appendices

Appendix I

A.I. Comparison of *ROC* Curves Test

The nonparametric *test of comparison of ROC curves* has been proposed by DeLong, DeLong, and Clarke-Pearson (1988). It is based on the comparison of the areas under the ROC curves associated with the two EWS models, denoted AUC_1 and AUC_2. The null of the tests corresponds to the equality of areas under the *ROC* curves, that is H_0: AUC_1=AUC_2. The test statistic is defined as:

$$
\hat{S}_1 = \frac{1}{T_0^2(T_1-1)} \sum_{i:y_i=1} \left(\begin{array}{c}
\left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_1 \right]^2 \\
\left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_1 \right] \\
\times \left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_2 \right] \\
\left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_1 \right] \\
\times \left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_2 \right] \\
\left[\sum_{j:y_j=0} K(\hat{p}_j, \hat{p}_i) - T_0 \times AUC_2 \right]^2
\end{array} \right). \qquad \text{(A.4)}
$$

$$K(\hat{p}_j,\hat{p}_i)=\begin{cases}1 & \text{if } \hat{p}_i<\hat{p}_j\\ \frac{1}{2} & \text{if } \hat{p}_i=\hat{p}_j\\ 0 & \text{if } \hat{p}_i>\hat{p}_j.\end{cases} \tag{A.6}$$

Appendix II

B.I. Data Set

There is no official currency crisis dating method similar to the one NBER proposes for recessions. Therefore, a crisis episode is generally detected when an index of speculative pressure exceeds a certain threshold. Many alternative indices have been developed and used for identifying currency crises. But they are all nonparametric termination rules that take into consideration the size of the movements in a combination of a number of series. Lestano and Jacobs (2004) compare several currency crisis dating methods, aiming to identify the one that recognizes most of the crises categorized by the IMF for the 1997 Asian flu. They

To check the robustness of our results to the dating method, we also consider the *Zhang* pressure index instead of the *KLRm*. It is defined as follows:

$$Crisis_{it} = \begin{cases} 1 \quad \text{if} \left(\begin{array}{l} \frac{\Delta e_{it}}{e_{it}} > \beta_1 \sigma'_{e_{it}} + \mu_{e_{it}} \quad \text{or} \\ \frac{\Delta r_{it}}{r_{it}} < \beta_2 \sigma'_{r_{it}} + \mu_{r_{it}} \end{array} \right. \\ 0 \qquad \text{otherwise.} \end{cases} \tag{A.9}$$

where σ_{eit}' is the standard deviation of ($\Delta e_{it}/e_{it}$) in the sample of ($t-36$, $t-1$), and σ_{rit}' is the standard deviation of ($\Delta r_{it}/r_{it}$) in the sample of ($t-36$, $t-1$). The thresholds are set to $\beta_1=3$ and $\beta_2=-3$. Contrary to the KLRm index, the interest rates are excluded from the ZCC and the thresholds used are time-varying for each component.

From a macroeconomic point of view, it is more important to know if there will be bank deposits, the real interest rate, the lending rate over deposit rate, and the real interest rate differential.

3 *Domestic real and public sector*: the industrial production index.

As in Kumar, Moorthy, and Perraudin (2003), we reduce the impact of extreme values by using the formula: $f(x_t) = sign(x_t) \times ln(1+|x_t|)$. Traditional first-generation (Im, Pesaran, and Shin, 1997 and Maddala and Wu, 1999) and second-generation (Bai and Ng, 2001 and Pesaran, 2003) panel unit root tests are performed, leading to the rejection of the null hypothesis of stochastic trend except for the lending rate over deposit rate and industrial production index indicators. Hence, these series are substituted by their first differences.

Finally, we identify the most correlated leading indicators for each country. Two indicators are considered as being correlated for a certain country if Pearson's

Appendix III

C.I. A Robust Estimator of the Variance of the Parameters

To compute robust estimators of the variance for logit models we use a sandwich estimator. Technically, the variance-covariance matrix of the estimators is asymptotically equal to the inverse of the hessian matrix: $\mathbb{V}(\hat{\beta}) = -H(\hat{\beta})^{-1}$ However, this is appropriate only if we employ the real Data Generating Process (DGP). For a more permissive method from this point of view, we define the variance vector as follows:

$$\mathbb{V}(\hat{\beta}) = (-H(\hat{\beta})^{-1})\mathbb{V}(g(\hat{\beta}))(-H(\hat{\beta})^{-1}), \tag{A.11}$$

where $H(\beta)^{-1}$ is the inverse of the hessian matrix, and $\mathbb{V}(g(\hat{\beta}))$ is the variance of the gradient. Using the empirical variance estimator of the gradient we find that:

About this article

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