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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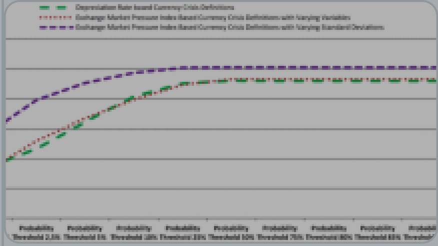

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and the crisis probabilities may exist. Nevertheless, this approach is not feasible in our context. Indeed, the accuracy and misclassification measures cannot be employed, as they have been used to identify the optimal cut-off and no other adequate measures have been proposed so far.

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

11. Berg and Cooke (2004) show that considering a forecast horizon larger than 1 leads to autocorrelation in the crisis variable. This stylized fact is confirmed by Harding and Pagan (2006).

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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Association Congress (Glasgow), the 2010 Econometric Society World Meeting (Shanghai), the 2010 meeting of the Association Francaise de Sciences Economiques (Paris), the 2010 business cycle meeting at Eurostat (Luxemburg) and the 2009 MIFN meeting (Luxemburg) for their questions and reactions. The usual disclaimers apply.

Electronic supplementary material

[Supplementary Tables](#)

Appendices

Appendix I

$$\underset{(2,2)}{\hat{\mathbb{V}}} = (T_1)^{-1} \underset{(2,2)}{\hat{S}_1} + (T_0)^{-1} \underset{(2,2)}{\hat{S}_0}, \tag{A.3}$$

where T_1 (respectively T_0) is the number of crisis (respectively calm) periods in the sample, and $\hat{S}_1$ (respectively $\hat{S}_0$) denotes the estimated variance for the crisis (respectively calm) periods.

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

$$\hat{S}_0 = \frac{1}{T_1^2(T_0-1)} \sum_{j:y_j=0} \begin{pmatrix} \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_1\right]^2 & \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_1\right] \times \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_2\right] \\ \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_1\right] \times \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_2\right] & \left[\sum_{i:y_i=1} K(\hat{p}_j,\hat{p}_i) - T_1 \times AUC_2\right]^2 \end{pmatrix}, \quad \text{(A.5)}$$

Following their results, we identify crisis periods using the KLR modified pressure index (KLRm), which, unlike the KLR index, also includes interest rates:

$$KLRm_{it} = \frac{\Delta e_{it}}{e_{it}} - \frac{\sigma_e}{\sigma_r}\frac{\Delta r_{it}}{r_{it}} + \frac{\sigma_e}{\sigma_{ir}}\Delta ir_{it}, \tag{A.7}$$

where e_{it} denotes the exchange rate (that is, units of country i's currency per U.S. dollar in period t), $r_{n,t}$ represents the foreign reserves, while ir_{it} is the interest rate. Meanwhile, the standard deviations σ_X are actually the standard deviations of the relative changes in the variables, $\sigma_{(\Delta X_{it}/X_{it})}$, where X denotes each variable separately, including the exchange rate and the foreign reserves, with $\Delta X_{it} = X_{it} - X_{i,t-6}$. For the interest rate, σ_{ir} is the standard deviation of the absolute changes in interest rate. For both subsamples, the threshold equals two standard deviations above the mean:[13]

serves as the crisis dummy variable taking the value of 1 if there will be a crisis in the following 24 months and 0 otherwise:

$$C24_{it} = \begin{cases} 1 & \text{if } \sum_{j=1}^{24} Crisis_{it+j} > 0 \\ 0 & \text{otherwise.} \end{cases} \quad \text{(A.10)}$$

At the same time, several explanatory variables from three economic sectors are considered (Lestano and Kuper, 2003) on a monthly frequency and denoted in U.S. dollars:

1. *External sector*: the one-year growth rate of international reserves, the one-year growth rate of imports, the one-year growth rate of exports, the ratio of M2 to foreign reserves, and the one-year growth rate of M2 to foreign reserves.

deposit rate, the first difference of the industrial production index, and yield spread are the least correlated ones with all the other indicators for all the 12 countries. The competing models are defined such that no couple of indicators is correlated in more than four countries. We hence identify the leading indicators by minimizing the AIC and BIC information criteria of the pooled panel data models, that is, growth of international reserves, growth of exports, growth of domestic credit over GDP, first difference of lending over deposit rate, first difference of industrial production index, and yield spread. The missing values through the series are replaced using cubic splines interpolation, but when the series revealed missing values at the beginning of the sample, such as "the one-year growth of terms of trade" or "yield spread," the corresponding observations are dropped from the analysis, leading to an unbalanced panel framework. Table 8 shows the period covered by the leading indicators for each of the 12 countries.

which is a robust variance estimator for the time-series model.

The main advantage of this sandwich method is that it can also be applied in the case of grouped data, as in our case. It is important to note that in the current situation, each country from a cluster is a group of time-series observations that are correlated. Thus, the observations corresponding to a country are not treated as independent, but rather the countries themselves which form the clusters, are considered independent. Therefore, instead of using $g_t(\beta)$, we use the sum of $g_t(\beta)$ for each country, while T is replaced by the number of countries in a cluster. These changes ensure the independence of so-called superobservations entering the formula (Gould and others, 2005).

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