The Good, the Bad, and the Ugly…signals of currency crises: Does signal approach work in ex-ante forecasting of currency crises?

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1. Introduction

How to construct an Early Warning System (EWS) which would forecast future currency crisis[1] episodes in an accurate and timely manner? First, one should select a list of the *Early Warning Indicators (EWIs)* – macroeconomic variables with different dynamics on the onset of currency crisis episodes, – as supported by theoretical models and empirical studies. Second, one should choose whether to use a *parametric* or a *non-parametric approach* to forecast an imminent crisis period. The former approach estimates the crisis probability using multivariate discrete choice models (i.e. $probit$ or $logit$ regressions) and assesses the predictive value of individual indicators based on their statistical significance. The latter approach monitors a list of EWIs and issues a crisis signal whenever the observed change in a variable passed a certain critical threshold.

Frankel and Rose (1996) were the first to apply parametric approach using the multivariate probit model. Kaminsky, Lizondo, and Reinhart (1998, henceforth - KLR[2]) and companion papers (Kaminsky and Reinhart, 1999; Goldstein, Kaminsky, and Reinhart, 2000) were the pioneers of the signal approach. Subsequent studies improved on either parametric or signal approaches via adding new variables, extending samples, and refining the models. For example, Milesi-Ferretti and Razin (1998) and Esquivel and Larrain (1998)[3] suggested alternative specifications for the probit model. Berg and Patillo (1999) found that the probit model was only slightly better than the KLR model, and both were more informed than a random guess[4]. Edison (2003) revisited the KLR approach and confirmed its value to identify the crisis vulnerabilities, although with such shortcomings as the high false alarm rate and inability to predict the exact timing of a crisis.

To choose which EWS is the most accurate, one should select and apply *the model superiority criteria*. Several measures were suggested in the current literature: the noise-to-signal ratio (NSR), the percentages of the correctly called crises and tranquile periods, the proportion of correctly classified periods in the total number of observations (KLR; Kaminsky and Reinhart, 1999; Edison, 2003), the quadratic

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[1] According to the conventions of the international finance literature, this chapter uses terms "currency crisis," "exchange rate crisis," "balance of payment crisis," and "currency crash" interchangeably.

[2] They also provided an extensive survey of the empirical studies of the EWIs up to 1998.

[3] They found that high rates of seignorage, current account imbalances, RER misalignment, low foreign exchange reserves, negative terms of trade shocks, poor growth performance, and a measure of regional contagion have significant predictive power to explain currency crises.

[4] They note that at the 50% cut-off, the KLR model correctly called only 9% of crisis episodes while sending 44% of false alarms. At the 25% threshold, fraction of correctly called episodes increased to 41% at the cost of higher false alarm rate (63%).

probability score (QPS) and its counterparts[5] (Kaminsky, 2000, 2003, 2006), and the total misclassification error (TME) (Comelli, 2014). Candelon, Dumitrescu, and Hurlin (2012) argued that the AUC criterion from the ROC curves analysis should be preferred over a traditional QPS in the context of the EWSs. Candelon, Dumitrescu, and Hurlin (2014) and Commelli (2014) used the AUC statistics to compare different parametric specifications of the EWSs. Drehmann and Juselius (2014) applied the ROC curves analysis and the AUC criterion to evaluate the signals of the banking crises, arguing that they have advantage when one evaluates crisis signals without knowing the policy-makers utility functions. Several other authors used the AUC statistics to assess the value of the parametric EWSs of the currency crises (i.e.; Catao and Milesi-Ferretti, 2013; Caggiano et al., 2014; Frost and Saiki, 2014; Comelli, 2014).

Up to date, neither parametric nor signal approach has established its superiority in forecast accuracy. The benefit of the parametric approach is that it estimates a probability of a future crisis episode. However, it does not help to choose what probability level should be used as a threshold to predict a crisis[6]. Besides, statistical significance of a model depends on the data availability for the crisis episodes with similar features; and a model can be subject to endogeneity concern.

The advantage of the signal approach is that it does not impose parametric structure on the data and is easy to implement. However, it still needs improvement. First, it currently counts signals as good if they were followed by a crisis episode in any month within *a crisis window*[7]. A preferred EWS would assess the predictive value of a signal with *a fixed forecast horizon*. Second, it marked an indicator as a relevant EWI if it produced the *NSR<1* at least for some values in a grid search. A better EWS would keep only indicators which take *consistently different values in the crisis and non-crisis episodes* (as measured by NSR<1 at the entire range of the EWIs range). Third, the published accuracy results depend on *the choice of the threshold* after reaching which an EWS issues a crisis signal. The current practice relies on the *minimum NSR* criterion and/or overall accuracy ratio. The former *minimizes the number of false alarms at the cost of missing many crisis episodes*; a preferred criterion would consider the trade-off between the false alarms and missed signals and aim to *maximize utility of the forecast user*. The latter is based on the proportion of correctly classified periods in the total number of observations and, therefore, gets *too much credit for the correct identification of tranquile times*, due to the rare nature of crisis episodes. An alternative measure would assess the EWS's ability to predict currency crisis episodes as events excluding the non-crisis episodes from the analysis. Finally, there is mixed evidence about *the out-of-sample performance* of the existing EWS.

This chapter contributes to the signal approach literature via addressing the problems stated above. It poses the following research questions: (i.) which economic indicators can accurately distinguish between

[5] These include the log probability score (LPS) and the global squared bias (GSB).
[6] Ideally, such probability value would exceed 50%. However, in practice, an analyst should predict a crisis when it exceeds 20-30%.
[7] For example, KLR used the 24-months window, Candalon focused on the 6-months one.

the future states (a crisis vs. a non-crisis one) in h=1, 3, 6, 9, 12, 18, and 24m horizons? (ii.) How to choose a critical threshold at which an EWI should issue a crisis? (iii.) How accurately can these EWIs predict incoming currency crisis episodes as events? (iv.) What is the difference between the in-sample and out-of-sample performance of the analyzed EWS? and (v.) What are the benefits of the forecast combinations using the ad-hoc rules?

The methodology of this study builds on the novel application of the ROC curves analysis. To address the first research question, I will compare the predictive value of the indicators within a fixed forecast horizon (h=1, 3, 6, 9, 12, 18, or 24 months). The statistical properties of the ROC curves and their use in evaluating predictive value of the binary classifiers was explained in the first chapter (see section 1.2.4 for details). I assume that each indicator (model) in contest of this chapter has an unobservable true ROC curve – the one that corresponds to the infinitely long time series, if we had such data. However, the sample is limited due to availability of macroeconomic data with monthly frequency, and the ROC curves in this study are only in-sample estimates of their true population counterparts. This chapter evaluates predictive value of the EWIs with the ROC curves analysis using the criteria established earlier in the first chapter (p.15, section 1.2.4): it focuses on the AUC statistics and its confidence intervals to assess the in-sample properties and the significance of the estimated ROC curve itself to measure the out-of-sample power.

The second research question emphasizes that the choice of a threshold value used to signal future crisis episodes affects the accuracy statistics and leads to a trade-off between the two types of errors: a missing signal and a false alarm. Following Candelon et al. (2014) and Jordà (2014), I use the ROC-optimal threshold values above which an indicator should signal an impending crisis. I also show algebraically that the ROC-optimal thresholds minimize the total misclassification cost and establish the relationship between the optimal thresholds in the traditional signal approach (as established by Kaminsky and co-authors) and those proposed here. Then, I compare the accuracy statistics at the alternative threshold values.

To answer the third question, I use a modified ROC curve so that it evaluates the accuracy of an EWS in predicting currency crises as events instead of assessing their power to produce binary classifications of future periods as the crisis or tranquil states. Stekler and Ye (2017) proposed to map the tradeoff between the signal's precision and the false alarm rate. I suggest an alternative variation of a modified ROC curve which focuses on the precision and the share of correctly called crisis episodes. The latter statistics is complementary to the false alarm rate.

To answer the fifth question and test the signal extraction EWS, I divide the data into the training and test sets. I use the training set (1970-1995) to evaluate the in-sample performance of individual EWIs, which I later apply to a test set (1996-2002) to assess the out-of-sample predictive value of the indicators chosen earlier.

Finally, I analyze four forecast combination rules. The first two rules combine information from different indicators at the same forecast horizon, sending a crisis signal when at least one (two) out of four good indicators send a signal. The other two rules combine information coming from the same indicator at several horizons (h=1, 3, 6, and 9m) and can be interpreted as results for the forecast windows as a signal is issued whenever there it is send for at least one (or two) horizons.

The methodology is discussed in Section 2. Section 3 describes the data. The empirical results are presented in Section 4. Section 5 concludes, followed by the references in 6.

2. Methodology: traditional signal approach vs. alternative

Constructing an EWS of currency crisis involves (i.) identifying dates of the crisis episodes; (ii) choice of the indicators; (iii.) choosing a forecasting rule and optimal threshold; and (iv.) evaluating the predictive value of the examined EWIs. While the first two steps are the same regardless the chosen signal approach EWS, there are some differences between the traditional and proposed alternative approaches in the last two stages.

2.1. Choice of Early Warning Indicators

The theoretical literature on the exchange rate crises suggests a broad set of such indicators. It groups the models of currency crises in three generations.

The "first generation" theories (i.e. Krugman,1979; Flood and Garber, 1984) believe that episodes of currency crashes stem from inconsistent macroeconomic policies (excessive fiscal and monetary expansions under the fixed exchange rate regime) which lead to a depletion of the foreign reserves and a speculative attack. The budget deficit, growing money supply and forward premium, RER overvaluation, and current account deficit usually precede such attacks.

The "second generation" model (see Obstfeld, 1996) looks at a currency crisis as an optimal choice of a policy-maker who is concerned about the recession, unemployment, or weak trade competitiveness. The weak GDP growth, RER appreciation, deterioration of terms of trade and current account deficit should signal such a crisis.

Theories of the "third generation" (i.e., Chang and Velasco, 2001) explain exchange rate crisis with problems in the banking sector, capital inflows, and financial liberalization, which are warned with increasing interest rates, high debt levels, and bank runs[8].

To limit the scope of this paper, I examine only indicators available on a monthly frequency[9] and chosen as good predictors of the currency crisis episodes by Kaminsky and co-authors (table 1)[10].

[8] When the central bank bailouts financial institutions via money creation, symptoms of the "first generation" currency crisis model will follow suit.
[9] GDP was interpolated to monthly values.
[10] The stock prices and terms of trade were excluded due to the data deficiency.

Table 1. The Early Warning Indicators and their expected critical shock areas.

#	Indicator	Problem and critical shock
1	Deviation of the RER from the trend	Current account/ Negative
2	Growth rates of the international reserves	Capital account / Negative
3	The excess real money (M1) balances	Monetary policy/ Positive
4	Growth rates of the broad money (M2) to foreign reserves ratio	Capital account/ Positive
5	Growth rates of the exports	Current account/ Negative
6	Growth rates of the index of industrial output	Growth slowdown/ Negative
7	Growth rates of the M2 money multiplier	Overborrowing cycles/ Positive
8	Growth rates of the domestic credit to GDP ratio	Overborrowing cycles/ Positive

All the variables are converted to real terms using CPI and measured as percent values. Two variables – the deviation of the RER from the trend and the excess real M1 balances – require additional calculations[11]. The positive critical shock means that an indicator issues a crisis period when it takes very high values; i.e., very fast increase in excess M1 balances, M2/reserves, M2 multiplier, credit-to-GDP ratio and real interest rate would foresee a future crisis period. The negative critical shock means that an indicator issues a crisis signal if it takes very negative values; this is true for large declines in the RER, exports, international reserves, and industrial output. Data for each indicator are pooled across countries and grouped in 100 percentiles.

2.2. Identification of currency crisis episodes

There are no commonly accepted currency crisis dates[12] as literature offers several ways to identify a currency crisis. For example, Kaminsky (2003, 2006) identified crisis episodes using the Exchange Rate Market Pressure Index (EMPI) [13] for each individual country[14] in-sample: a period is marked as a crisis (Y=1) if the EMPI deviates from its mean (μ_{EMP}) by more than 2.5 standard deviations (σ_{EMP}), and as a

[11] To measure the deviation of the RER from the trend, I first estimate the RER using quadratic trend ($RER_n = \beta_0 + \beta_1 n + \beta_2 n^2 + e_n$), and then find the deviation between the actual and fitted RER values. The excess real M1 balances are found as the difference between the estimated demand for real M1 balances ($M1real_n = \beta_0 + \beta_1 realGDP + \beta_2 Inflation + \beta_3 n + e_n$) and their actual supply, expressed as a percentage.

[12] Lestano and Jacobs (2007) demonstrated that no single method could identify all the crisis dates as accepted in the IMF chronology for the Asia crisis 1997-1999.

[13] There are several alternative ways to calculate the EMPI. For example, Kaminsky and Reinhart (1999) calculated it as $EMPI_{it} = \frac{\%\Delta e_{it}}{e_{it}} - \frac{\sigma_e}{\sigma_{fxr}} \frac{\%\Delta fxr_{it}}{fxr_{it}}$, where e_{it} is a bilateral nominal exchange rate between an i-country's domestic currency and a country-issuer of the international reserve currency to which a country's currency is pegged, fxr_{it} is a stock of the country "i" foreign exchange reserves, while σ_e and σ_{fxr} are their standard deviations. Thus, the first term stands for the percentage change in the exchange rate, while the second term accounts for the negative percentage changes in the gross international reserves. Thus, the EMPI account not only for the episodes which ended up in the exchange rate adjustment, but also cases of the speculative attack which resulted in the loss of international reserves without devaluation due to the interventions of the country's central bank in a foreign exchange market.

[14] All crisis episodes are identified as single country events.

non-crisis (Y=0) otherwise. Other authors established the ad-hoc rules based on the rate of the currency devaluation or the loss in the foreign reserves. Both approaches are data-dependent: one will likely get more favorable results when the same data are used to identify the crisis episodes and to produce predictions. To provide objective analysis, I refrain from creating an own crisis ID variable, adopting the crisis dates published in Kaminsky (2003, 2006).

2.3. Traditional Signal Approach EWS: Kaminsky and co-authors

The traditional signal approach EWS classifies future periods as a crisis ($\hat{Y} = 1$) or non-crisis ($\hat{Y} = 0$) state based on comparison of an EWI value with a chosen threshold. The thresholds $t \in [0, 100]$ are expressed as percentiles. The percentiles are found after pooling all data across countries per each indicator, sorting them from the lowest to the highest values, and grouping into 100 percentiles. The training sample is used to determine the optimal thresholds expressed in terms of percentiles (the alternative optimality criteria will be explained later). Then an analyst finds the growth rate corresponding to the optimal percentile and uses it in the out-of-sample exercise.

When a theory suggests that a positive shock to the variable might cause a crisis, the analyst should use the following forecasting rule[15]:

$\hat{Y} = 1$ (a crisis is forecast for a chosen horizon) if $g_{EWI} \geq t$ [1]

$\hat{Y} = 0$ (a crisis is not forecast for a chosen horizon) if $g_{EWI} < t$

The forecasting rule in [1] will result in two kinds of correct predictions: *the true positives*, which count the number of times when the issued signal correctly classified future period as a crisis state, and are often named the "good signals," and *the true negatives* count correctly identified non-crisis periods, which are of the least interest to the forecast users. Inevitably, such a rule will also produce two types of misclassifications: *the false positives*, which measure the number of tranquil periods misclassified as crisis ones, and are also called "false alarms," and *the false negative*s, which indicate the number of missed crisis episodes when the forecasting rule failed to issue a signal about the impending crisis. For any threshold t, correct predictions and misclassifications can be organized in the 2x2 contingency table presented below.

Figure 1. Contingency table for crisis forecasts.

		Forecasts		Total in rows
		$\hat{Y} = 1$	$\hat{Y} = 0$	
Actuals	$Y = 1$	TP	FN	$TP + FN$
	$Y = 0$	FP	TN	$FP + TN$
Total in columns		$TP + FP$	$FN + TN$	$n = TP + FP + FN + TN$

[15] If the theory reveals that a variable indicates the impending crisis when it takes values from the lower tail of its distribution, the signs in the forecasting rule [16] change to the opposite.

KLR 1998 use a similar contingency table, but the rows and columns are reversed. They name the true positives (TP), false positives (FP), and false negatives (FN) as good, bad, and missing signals, respectively. Missing signals are the "ugly" ones: currency crisis episodes incur very high losses when come unnoticed. And what about the true negatives (TN) – those tranquil times that were correctly expected as tranquil? In fact, no one cares about those! KLR denote TP, FP, FN, and TN as A, B, C and D, respectively. Note, that missing signals relate to type I statistical error: one rejects a null hypothesis of a crisis when it is true. Issuing a bad signal (also called in KLR1998 as false alarm) means to make a type II statistical error: one fails to reject a null hypothesis of a crisis when it is not true. The numbers in the contingency table can be used to calculate a number of accuracy measures. Traditional signal approach focused on the assessment of the NSR. For example, KLR calculated the NSR for each indicator over all values $t \in [80, 90]$[16]:

$$NSR\ (t) = \frac{\text{fraction of tranquile periods incorrectly identified}}{\text{fraction of crisis periods correctly identified}} == \frac{FPR}{TPR} \qquad [2]$$

$$= \frac{FP}{(FP + TN)} : \frac{TP}{(TP + FN)} = \frac{FP}{TP}\frac{(FP + TN)}{(TP + FN)} = \frac{FP}{TP}\frac{n(Y = 1)}{n(Y = 0)}$$

KLR pick a threshold as optimal if it minimizes the NSR. They also consider all indicators with $\min NSR < 1$ as the EWIs with strong predictive value[17]. Additionally, they evaluated the probability of a crisis conditional on a signal issued as $\frac{TP}{TP+FP}$ at t^{NSR} (this measure is known in statistics as precision).

The traditional approach outlined in this section has some drawbacks. First, it does not have a fixed forecast horizon: a signal is marked as good if a crisis period occurs in any of the next 24 months after its issuance. Thus, it is not conclusive about the lead time of the assessed indicators and overstates the indicator's predictive value, while understating the number of false alarms. Second, the minimum NSR<1 is a necessary but not a sufficient criterion to choose an EWI: it does not tell if a variable behaves consistently differently in crisis vs. non-crisis episodes. Third, it does not assess the out-of-sample predictive value of an EWI. Then, the percentile variable is defined for each indicator-country individually, forcing the EWS to produce equal number of crisis signals for every country. Finally, the overall accuracy measure is too optimistic as it takes too much credit for the non-crisis periods not preceded by the signal.

This chapter offers an *alternative non-parametric approach to building an EWS of the currency crisis episodes* the *ROC curves*[18]. First, it utilizes the *traditional ROC curves* to evaluate whether an indicator has *binary classification abilities to distinguish crisis periods from tranquil ones*, and then use the *modified ROC curves* to assess the *value of an indicator in forecasting crisis episodes as events*.

[16] Alternatvely, t ∈[10, 20] perecentiles if the lower values indicate the higher probability of a crisis.
[17] See Kaminsky, Lizondo, and Reinhart (1998), p.20, for the author's definitions.

[18] See Pepe (2000), Pepe et al. (2009), Krzanovski & Hand (2009).

2.4. Alternative Signal Approach EWS: advantages of the ROC curves analysis

The alternative approach proposed in this chapter uses a forecasting rule similar to the one in [1], with a few notable distinctions. First, instead of focusing on the 24-months crisis window, it uses the fixed n-months ahead forecast horizon (n=1, 3, 6, 9, 12, 18, and 24), which is a stricter way to evaluate predictive power of the indicators. Second, all the indicators are transformed[19] (if necessary) so that they take higher values in crisis. Third, the percentiles for each indicator were found after pooling data for all countries unlike the KLR who used individual distribution for each country[20]. Finally, the predictive value of an indicator is assessed at the entire range of the threshold values $t \in [0,100]$. This is because a strong EWI should consistently take higher values in crisis periods and lower values in the non-crisis periods. Thus, it should signal better than a random guess regardless of the chosen value t.

For every value $t \in [0,100]$, the forecasting rule will issue a crisis signal when the indicator exceeds the chosen threshold. The correct predictions and misclassifications form a 2x2 contingency matrix as explained above. In the context of this chapter, every contingency table yields unique combinations of the TPR and FPR, which measure the probabilities of sending a crisis signal conditionally on the observing actual non-crisis and crisis periods, respectively:

$$FPR(t) = p(g_{EWI} \geq t | Y = 0) \qquad [3]$$

$$TPR(t) = p(g_{EWI} \geq t | Y = 1)$$ [21]

Evaluating the TPR and FPR at various values of a threshold t, one can obtain an ROC curve (see Fig.2), which was discussed in detail in chapter 1. The AUC statistics here measures a probability that an indicator will take on values which are significantly higher in crisis periods than in tranquil ones.

In this study I apply the following criteria of the in-sample and out-of-sample predictive value. An indicator meets the in-sample predictive value criterion for a range of thresholds t if its ROC curves is above the chance diagonal for that range of t; this quality maybe sample-dependent, An indicator is said to have an out-of-sample predictive value, if the lower confidence interval of its ROC curve is also above the chance diagonal.

An indicator which meets the in-sample predictive value criteria in a training set is said to be able to classify between the crisis and non-crisis periods in sample significantly better than a random guess.

[19] This requires the change of the sign for the indicators with negative critical areas.

[20] KLR determined percentiles and corresponding growth rates on a country by country basis. Thus, the same percentile value will correspond to different growth rates. This method forces equal number of crisis signals for each country regardless of its fundamentals. This study finds percentile values after polling data for all countries. Therefore, it looks at the overall distribution of growth rates across countries, and searches for the extreme growth rate above which to issue a crisis signal. It yields one growth rate which forecaster will use to predict the future crisis. This is more realistic (a country with worse fundamentals is more likely to have a crisis) and simple (there is a single growth rate to use in out-of-sample test set). The conclusions about indicators are robust to the definition of the percentile variable, although the individual percentiles yielded slightly worse accuracy statistics.

[21] The FPR and TPR correspond to the nominator and denominator of the NSR presented in formula [17].

Then I use a test set to assess the out-of-sample predictive value for the indicators which demonstrated in-sample predictive value in a training set.

The NSR in the traditional signal approach equals the inverse of the slope of the ROC curve. Therefore, all points on the ROC curve at which NSR<1 will lie above the chance diagonal, while the optimal threshold t^{NSR} will correspond to a point where the ROC curve has the steepest slope[22]. This observation implies that the NSR<1 criterion is a necessary but not a sufficient condition to conclude that a variable is a good EWI. The ROC curves analysis implies that the threshold t is optimal (t^{ROC}) when it maximizes the vertical distance between the ROC curve and the chance diagonal (MVD), also known as the Youden index (J)[23].

$$\mathrm{MVD(t)} = J(t) = TPR(t) - FPR(t) = TPR(t) + TNR(t) - 1 \qquad [4]$$

One can easily show that maximizing the J-index is equivalent to minimizing the sum of the type I and type II errors (TME=FPR+FNR)[24]. Note, that optimal threshold t^{ROC} implied by the ROC analysis relies on the different criteria when compared to the traditional signal approach. The choice of the optimality criteria affects the entries of the contingency table, and therefore the accuracy ratio (see formula 8 in chapter 1).

2.5. Choice of the optimal threshold: traditional vs. alternative approach

This section establishes the relationship between the optimal threshold in the traditional signal approach t^{NSR} and the optimal threshold in the proposed alternative signal approach t^{ROC}.

Proposition. Let t^{NSR} be an optimal threshold which minimizes the NSR, and t^{ROC} - an optimal threshold which maximizes the Youden index. Then the following inequalities will hold:

$$t^{NSR} \geq t^{ROC} \qquad [5]$$

$$TPR(t^{NSR}) \leq TPR(t^{ROC})$$

$$FPR(t^{NSR}) \leq FPR(t^{ROC})$$

Proof of proposition:

1. Since t^{NSR} minimizes NSR, it implies that $\frac{FPR(t^{NSR})}{TPR(t^{NSR})} \leq \frac{FPR(t^{ROC})}{TPR(t^{ROC})}$. Let $k \leq 1$ be a coefficient, and rewrite the previous condition as

[22] The same point will maximize the positive likelihood ratio since $LR+= \frac{p(t|Y=1)}{p(t|Y=0)} = \frac{TPR(t)}{FPR(t)} = \frac{1}{NSR(t)}$.

[23] It is also equivalent to the Kolmogorov-Smirnov statistics (KS), which is used to test whether the two distributions are different. In this chapter, we test whether the values if the analyzed leading indicator belong to two different states - crisis and tranquil.

[24] First note that the FPR and FNR represent the errors of type I and II, given the null hypothesis of a non-crisis period. Then rewrite [4] using complementarity of the TPR with the FNR and the TNR and the FPR as $MVD(t) = \left(1 - FNR(t)\right) + \left(1 - FPR(t)\right) - 1 = 1 - \left(FNR(t) + FPR(t)\right) = 1 - TME(t)$

$$\frac{FPR(t^{NSR})}{TPR(t^{NSR})} = k\frac{FPR(t^{ROC})}{TPR(t^{ROC})} \quad [6]$$

2. Since t^{ROC} maximizes the J index, it implies that

$$J^{ROC} = TPR(t^{ROC}) - FPR(t^{ROC}) \geq TPR(t^{NSR}) - FPR(t^{NSR}) = J^{NSR} \quad [7]$$

3. Use [6] to rewrite $FPR(t^{NSR})$ and plug in [7] to obtain

$$J^{NSR} = \frac{TPR(t^{NSR})}{TPR(t^{ROC})}[TPR(t^{ROC}) - k\, FPR(t^{ROC})] \geq \frac{TPR(t^{NSR})}{TPR(t^{ROC})}J^{ROC} \quad [8]$$

since $[TPR(t^{ROC}) - k\, FPR(t^{ROC})] \geq [TPR(t^{ROC}) - FPR(t^{ROC})] = J^{ROC}$

4. Both [7] and [8] may hold simultaneously if and only if $\frac{TPR(t^{NSR})}{TPR(t^{ROC})} \leq 1$, which implies

$$TPR(t^{NSR}) \leq TPR(t^{ROC}) \quad [9]$$

5. Both the true and false positive rates are decreasing in t: $\frac{dTPR(t)}{dt} < 0$; $\frac{dFPR(t)}{dt} < 0$[25]. Therefore, $t^{NSR} \geq t^{ROC}$.

Thus, we have established that the ROC-implied threshold t^{ROC} is less or equal then an optimal threshold suggested by the traditional signal approach t^{NSR}.

An analyst who picks a low cut-off value t will likely detect many crisis episodes but also issue many false alarms. This choice results in both high TPR and high FPR. Such a forecasting strategy can assist a forecast user who has high costs from missing a crisis but low costs from sending a false alarm. For example, an official authority would prefer to pay attention even to the small signals, because this could allow to implement the appropriate preemptive measures and regulations and to prevent the macroeconomic losses. Therefore, such authority should sacrifice high false alarm rate to minimize the missing crisis episodes.

On the opposite, private investors might lose profits if they issued many false alarms. Thus, they may prefer forecasting crisis periods using higher thresholds. This choice would result in lower TPR and lower FPR, while increasing the rate of correctly called tranquility periods (TNR) and the rate of missed crisis episodes (FNR).

Jordà[26] (2014) demonstrated that the ROC-implied threshold maximizes the forecast-user's utility function even when it is unknown. This implies that choosing a forecasting rule with a different threshold (i.e. t^{NSR}), the forecast-user will lose utility.

2.2.6. Modified ROC curves analysis: evaluating EWI's skill to forecast crises as events

When dealing with rare events such as a currency crisis, one can achieve higher accuracy statistics

[25] See, for example, Krzanovski and Hand (2009) for the reference.
[26] He modified the ROC curve replacing the FPR with the TNR on the horizontal axis. This transformation does not change the optimal threshold because the TNR and FPR add to one (TNR=1-FPR).

due to the high number of true negatives (non-crisis periods correctly predicted as such). However, the forecast users are more interested to know how accurately the signal approach predicts crisis episodes. Evaluating an EWI based on its ability to distinguish between crisis and non-crisis periods only confirms that such an indicator can be used to classify a period in two types, but it does not tell how many crisis episodes it forecasted correctly. The need to count the number of crisis episodes as events (regardless of their duration[27]) can be addressed using a modified ROC curve.

Then the following statistics are created[28]:

- True signals, as the number of crisis episodes we successfully predicted in a total number of crisis episodes;
- False signals, as the number of false signals issued when crisis episode did not occur;
- Missed signals, as the number of crisis episodes that occurred without a signal issued.

These true, false and missed signals measures are similar to the TP, FP and FN numbers discussed earlier. In addition to the true and false positive rates, calculated in the same. An analyst who wants to measure the percentage of correct signals among all crisis signals sent will calculate precision in detection of crisis periods:

$$Precision = \frac{TP}{N_{\hat{Y}=1}} \qquad [10]$$

Stekler and Ye (2017) adopted a modified ROC curve known in the statistics as the precision-recall (PR) curve. They argued that it is a proper way to evaluate a leading indicator when the frequency of the event of interest is very low. They, however, deviated from the customary PR curve used in the literature focusing on the relationship between the precision and the false alarm.

This chapter adopts a traditional use of the PR curve as a mapping of the TPR values on the horizontal axis into the precision on the vertical axis. It illustrates the trade-off[29] between the recall (TPR) and precision: to achieve a higher recall of crisis events[30], the analyst needs to choose a lower threshold t. This will issue many false alarms, often lowering precision.

It is not easy to compare the accuracy of two forecasts from the same forecasting rule at two different thresholds as one can have higher precision but lower recall, and another – lower precision but higher recall. To address this issue, I measure a harmonic mean of two values, known in the machine

[27] In this research, no crisis periods lasted longer than 1 month.
[28] Note, that such classification leaves us without true negatives – because we are not interested in forecasting non-crisis periods.
[29] However, the relationship between the recall and precision is not monotonic. This is because the recall rate is monotonically decreasing in the value of a threshold t. However, there is no monotonic relationship between the value of the threshold t and the precision of a crisis signal. A higher t will increase precision if it adds more correctly identified crisis events than false alarms.
[30] Every crisis month is considered as an event.

learning literature as G-score:

$$G = \sqrt[2]{Precision * TPR} \qquad [11]$$

The higher G will imply higher overall predictive value of an indicator at chosen threshold.

2.7. Forecast combination rules

I analyze four forecast combinations rules using only those indicator-horizon pairs for which I found both in- and out-of-sample predictive value. Rules "At-Least-One-Indicator" (1-I) and "At-Least-Two-Indicators" (2-I) combine information derived from different indicators at the same horizon, as a given crisis can be preceded by different vulnerabilities. Rule 1-I issues a crisis signal when at least one of strong indicators issues a signal. Rule 2-I is stricter, requiring at least two indicators to issue a simultaneous signal. Rules "At-Least-One-Horizon" (1-H) and "At-Least-Two-Horizons" (2-H) combine information obtained from the same indicator at different horizons. Rule 1-H issues a crisis signal when an indicator exceeded a specified threshold at least at one horizon. Rule 2-H required an indicator to signal vulnerability at least at two horizons. Evaluating an EWI based on its ability to distinguish between crisis and non-crisis periods only confirms that such an indicator can be used to classify a period in two types.

3. Data on currency crisis episodes and dates

To evaluate results in the signal approach studies, mainly by Kaminsky and Reinhart (1999), this chapter replicates and extends their dataset. The monthly data are collected from the IMF IFS database, complemented with Kaminsky (2003) for missing observations. The growth rates[31] in the M2/reserves ratio[32], M2 multiplier, and domestic credit to GDP ratio, along with the excess demand for M1 balances, have positive critical areas. The growth rates of exports[33], foreign reserves, and industrial production index (IPI)[34], along with the deviation of the RER from the trend have negative critical areas. Thus, their signs are reverted.

The training set includes 76 crisis episodes in 20 countries over 1970m1-1995m12. The test set spans over 1996m1-2003m6 in 18 countries, 15 of which experienced 23 crisis episodes[35]. The unconditional probability of a BOP crisis was 1.22% in the training and 1.36% in a test set. Table A1 in Appendix list countries and the currency crisis dates.

4. Empirical results

4.1. Ability to classify periods as crisis and non-crisis ones

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[31] All growth rates are annual, on the month-to-month basis. KLR argued that such filtering makes data comparable across countries, ensure stationarity and well-defined moments, and remove seasonality effects.

[32] M2 was converted into USD.

[33] The value of exports is measured as a "free on board (FOB)", in millions USD.

[34] When general IPI was not available, it was replaced with the following indexes: Brazil (seasonally adjusted IPI), Peru & Philippines (general manufacturing index), Argentina, Bolivia, Colombia, Ecuador, Venezuela (crude petroleum production index).

[35] Finland and Spain joined the euro. Six countries did not have a crisis identified in the test set.

4.1.1. Evaluating the EWIs using the ROC curves analysis

Figure 2 below presents the ROC curves for each indicator across horizons. Its upper panel implies that the excess M1 balances, industrial production, domestic credit to GDP ratio, and money multiplier do not pass the in-sample value conditions for the EWI: their ROC curves are not entirely above the chance diagonal, and the AUC values are not significantly greater than 0.5. These indicators are excluded from the further analysis.

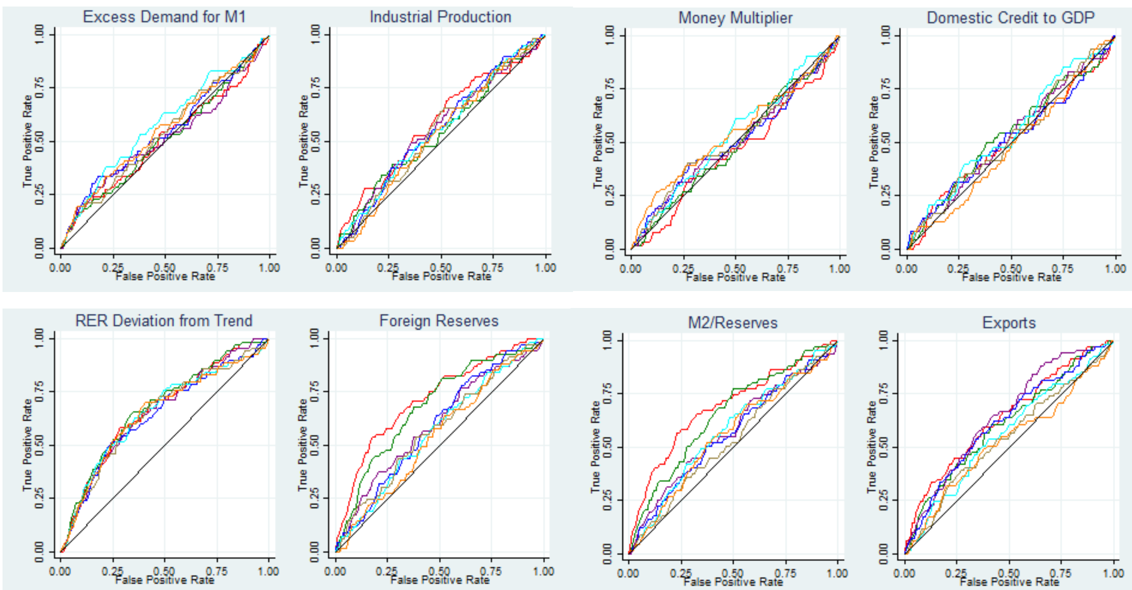

Figure 2. In-sample predictive value of the indicators across horizons.

The lower panel of Fig.2 shows four indicators for which the ROC curves which were entirely above the chance diagonal with the AUC values significantly above 0.5: 1) the RER overvaluation - at all horizons (AUC=0.65-0.67 with 95% confidence intervals from 0.58 to 0.73); 2) foreign reserves only at h≤18m (AUC=0.57-0.72), with significantly better results at h=1m and 3m; 3) M2/reserves at h<=12m; and 4) exports at h<=9m. Therefore, these indicator-horizons have the in-sample predictive value as they exhibited consistently different behavior in the crisis and non-crisis periods.

Fig.3 below shows that at h=1m forecast horizon, the ROC curves with their 95% confidence borders for RER overvaluation and decline in foreign reserves were entirely above the chance diagonal for any FPR value, suggesting their out-of-sample power to classify periods into crisis and non-crisis ones. However, for the M2/reserves ratio and exports declines the lower confidence border of the ROC curve was below the chance diagonal in the upper right corner, corresponding to the threshold values $t \in [0, 17]$ percentiles. The out-of-sample forecast ability of these indicators is analyzed via the significance of their ROC curves, presented in Fig.A1-A3 of Appendix for the longer horizons.

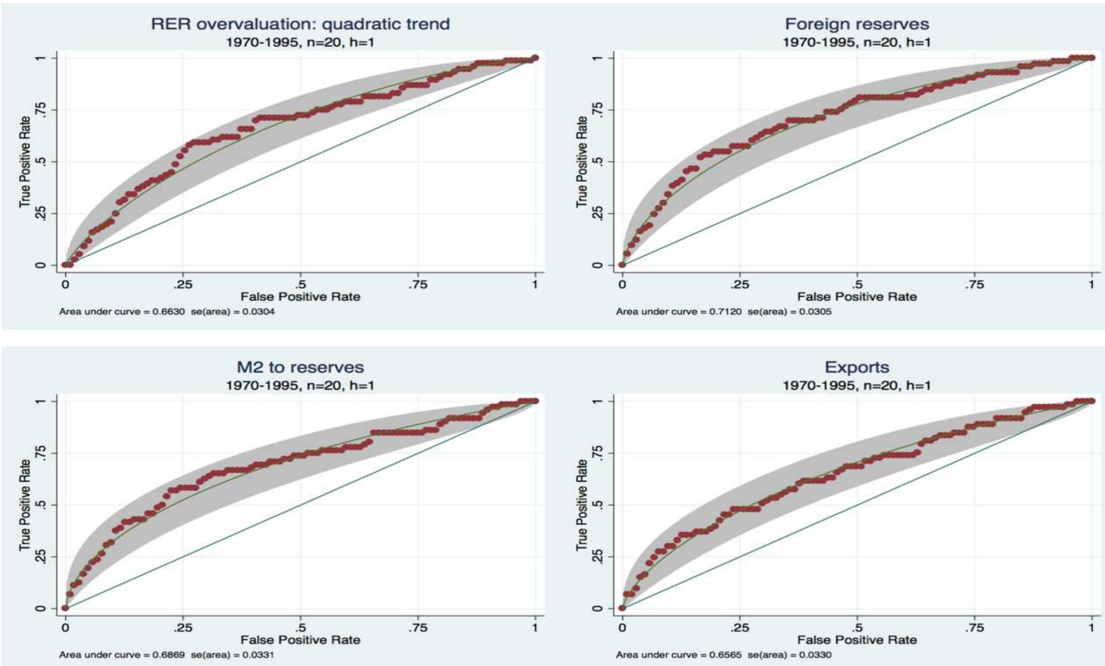

Figure 3. Out-of-sample classifying ability for indicators with in-sample value (h=1m)

Table 2 below provides details on the AUC statistics, lists the threshold ranges significant out-of-sample, and compares the optimal thresholds implied by the ROC and NSR criterions.

Table 2. ROC statistics for the indicators with in-sample predictive value[36]

Indicator	ROC statistics	Fixed forecast horizon, months						
		1	3	6	9	12	18	24
Overvaluation of the RER	AUC (std. error)	0.6630* (0.0304)	0.6720* (0.0310)	0.6580* (0.0302)	0.6343* (0.0331)	0.6371* (0.0347)	0.6442* (0.0335)	0.6322* (0.0353)
	t's significant out-of-sample	0-100	0-100	0-100	15-100	29-100	19-100	25-100
	Optimal threshold: t^{ROC}	73	67	55	75	64	67	57
	Optimal threshold: t^{NSR}	89	87	84	90	87	88	90
Decline in foreign reserves	AUC (std. error)	0.7120* (0.0305)	0.6726* (0.0313)	0.6059* (0.0343)	0.6092* (0.0316)	0.5759* (0.0323)	0.5788* (0.0340)	0.5395 (0.0330)
	t's significant out-of-sample	0-100	0-100	38-100	0 – 83	None	None	None

[36] These results are comparable to KLR who found that the optimal thresholds for the RER overvaluation, foreign reserves, M2/reserves ratio, and decline in exports were at 90, 85, 87, 90 and percentiles respectively (using 24-months window).

	Optimal t^{ROC}	83	64	80	53[37]	X	X	X
	Optimal t^{NSR}	90	89	88	80	X	X	X
Growth in M2/reserves ratio	AUC (std. error)	0.6869* (0.0331)	0.6572* (0.0319)	0.6004* (0.0363)	0.5824* (0.0362)	0.5741* (0.0329)	0.5588 (0.0330)	0.5379 (0.0356)
	t's significant out-of-sample	17-100	0-100	53-100	62-100	None	None	None
	Optimal t^{ROC}	78	52	73	64	X	X	X
	Optimal t^{NSR}	90	89	90	87	X	X	X
Decline in exports	AUC (std. error)	0.6565* (0.0330)	0.6174* (0.0335)	0.6335* (0.0309)	0.6048* (0.0335)	0.5606 (0.0342)	0.5396 (0.0358)	0.5184 (0.0369)
	t's significant out-of-sample	17-100	33-100	0-100	29-100	None	None	None
	Optimal t^{ROC}	77	59	57	67	X	X	X
	Optimal t^{NSR}	90	90	86	88	X	X	X

It confirms that the significance of the ROC curve is a stricter condition than the significance of the AUC statistics. For example, in the given sample, the rates of decline of foreign reserves had the AUC values significantly above 0.5 at h=12 and 18m. Thus, they had the in-sample value in classifying the crisis and tranquile periods. However, the lower confidence border of its ROC curve was entirely below the chance diagonal (see Fig. A3 in Appendix). Thus, should the exercise be repeated, decline in exports would not be able to classify two types of periods reliably.

The foreign reserves, M2/reserves, and exports were significant at the wide ranges of the thresholds for $h \leq 9$ months. The RER overvaluation was significant at all horizons, while no other variables had significant ROC curves at 1-year and longer horizons. This, however, is not bad news, because taking preemptive measures too early entails a risk of causing a self-fulfilling crisis and raises costs of crisis preemption. Further analysis will focus on the shorter horizons (h=1…9m ahead), as this period is sufficient to implement anti-crisis measures and eliminates long-run uncertainty about economic developments.

The ROC curves in Fig. 3 above demonstrated that excess M1 balances, industrial production, money multiplier and domestic credit to GDP did not display different behavior in crisis and non-crisis periods when evaluated at the fixed horizons. However, Kaminsky and her co-authors and followers concluded that these indicators are strong because they assessed their predictive value using the 24-months window, counting any signal in this period as a hit regardless of the horizon at which it was sent. To explain the difference in these conclusions, I propose to use *alternative convex ROC hull curves*[38] for the 24-months crisis window.

[37] This is under a restriction of t>=51 since the unrestricted ROC-t value was equal to 41.

[38] In past, the convex ROC curves were used to produce a forecast randomly choosing between the two indicators. See Krzanowsky and Hand, p. 145-147.

4.1.2. Comparison of traditional and alternative signal approaches using the ROC curves

The alternative convex ROC hull curves for the 24-months' forecast window (Figure 4) are constructed as convex combination of the best TPR for each percentile value at seven fixed forecast horizons (h=1, 3, 6, 9, 12, 18, 24 months) using the training sample. Note, that these ROC curves are more conservative than the ones we would get if used the same data and a search algorithm as in Kaminsky et al. (2000). This is due to the following reasons: 1) if one created the convex hull of all 24 ROC curves, one for each h=1, 2…24m ahead, its AUC would be greater; 2) the resulted optimal thresholds t may be different; 3) Kaminsky et al. (2000) added the signals from each horizon, the convex hull takes the strongest signal for each threshold.

The convex hull ROC curves presented below in Fig.4 are sufficient to explain why the two approaches yield different results. When one combines signals from seven forecast horizons, the corresponding ROC curves lie completely above the chance diagonal hiding the fact that the indicators do not have strong classifying ability at the fixed horizons.

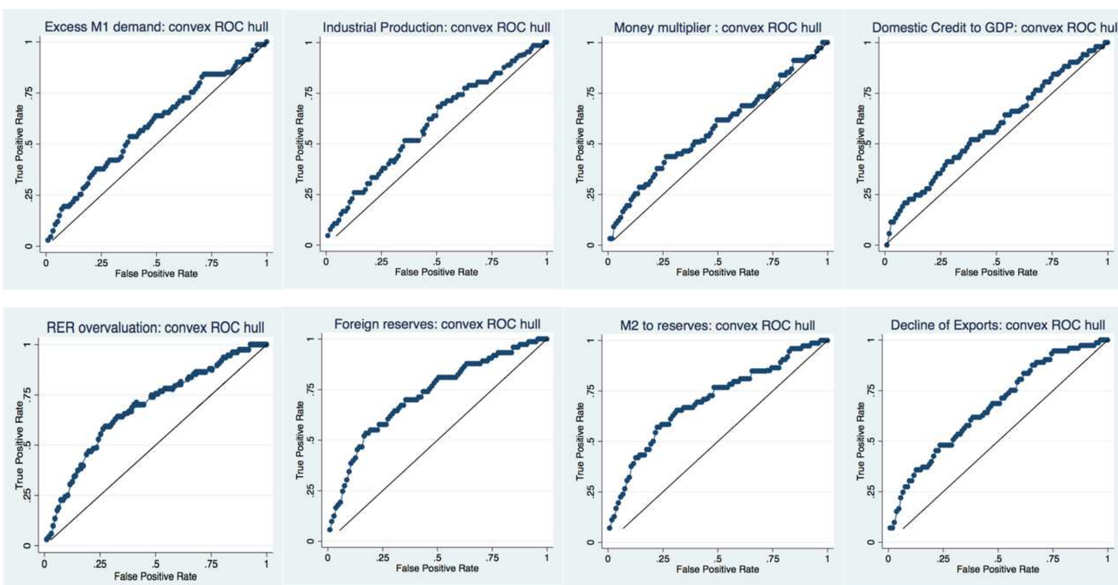

Figure 4. Convex hull ROC curves for the 24-months' forecast window horizon

Table 3 below shows that the convex (over horizons) hull ROC curves for all indicators have in-sample predictive value (AUC>0.5) which means that they issued useful signals at least at one horizon during the 24-month forecast window. However, none of these indicators send a signal at h=24m ahead fixed horizon. In fact, many of them signaled only at h=1m ahead.

Table 3. AUC statistics and optimal thresholds for convex hull of each indicator

Convex hull for "any of h=1, 3, 6, 12, 18, or 24 months" horizon	AUC	Std. Err.	95% Conf. Interval		Optimal threshold and horizon		Kaminsky & Reinhart (2000)
					Max J	Min NSR	
RER deviation from the trend	0.6823	0.0541	0.5762	0.7883	73 (1m)	93 (3m)	90 (1-24m)
Foreign reserves	0.7178	0.0024	0.7131	0.7226	83 (1m)	99 (1m)	85 (1-24m)
M2 to reserves	0.6969	0.0024	0.6923	0.7016	78 (1m)	99 (1m)	87 (1-24m)
Decline of exports	0.6673	0.0027	0.6620	0.6725	77 (1m)	97 (1m)	90 (1-24m)
Excess demand for M1	0.5866	0.0027	0.5813	0.5918	63 (12m)	94 (24m)	94 (1-24m)
Industrial production	0.5976	0.0033	0.5911	0.6041	50 (1m)	99 (1m)	89 (1-24m)
Money multiplier	0.5732	0.0026	0.5681	0.5783	74 (18m)	98 (24m)	86 (1-24m)
Domestic credit to GDP	0.5784	0.0028	0.5729	0.5839	73 (12m)	98 (6m)	90 (1-24m)

A preferred method is to evaluate each indicator-horizon pair and forecast crisis episodes as events only using those indicators and threshold ranges that have out-of-sample significance.

4.2. In-sample ability to predict crisis episodes as events: modified ROC curves

Table 3 above indicates that the ROC and NSR criteria implied that their respective optimal thresholds are $t^{ROC} = 73$ and $t^{NSR} = 89$ percentiles. Fig. 5 below compares two contingency tables which one would obtain using these threshold values in the forecasting rule. Its left panel shows that a forecast user following the ROC-criterion would issue a signal about the crisis period when the RER reaches 73rd percentile. This would correctly identify 59% of crisis episodes (45 out of 76) and marking 27% of the tranquile periods as crisis ones, issuing 1685 false alarms. As a result, precision of the signals sent would reach only 2.6%.

$t^{ROC} = 73$		Forecasts		Total
		$\hat{Y} = 1$	$\hat{Y} = 0$	
Actuals	Y=1	TP=45	FN=31	76
	Y=0	FP=1685	TN=4459	6144
Total		1730	4490	6220

$t^{NSR} = 89$		Forecasts		Total
		$\hat{Y} = 1$	$\hat{Y} = 0$	
Actuals	Y=1	TP=23	FN=53	76
	Y=0	FP=712	TN=5432	6144
Total		735	5485	6220

Figure 5. Contingency tables for the RER overvaluation at two alternative thresholds

The right panel of Fig. 5 indicates that a forecast user following the NSR criterion would issue a signal about the crisis period when the RER reaches 89th percentile. This would correctly identify only 30% of crisis episodes (23 from 76) and mark 12% of non-crisis periods as crisis ones, issuing 735 false alarms. Precision of the signals sent would slightly increase to 3.1%, although at the cost of missing 53 crisis episodes, compared to only 31 when the ROC criterion was used.

One may be tempted to compare the overall accuracy statistics, which is higher at the NSR-implied threshold (88%) than at the ROC-implied threshold (72%). However, when the frequency of the event of interest is very low, the accuracy statistics is almost equal to the share of correctly identified traquile periods (the TNR), which reached 73% and 88% for the two alternative threshold values. A forecast user who places more cost on the false alarms could prefer to choose a threshold above the t^{ROC}, but below t^{NSR}. Table 17 below presents the entries of the contingency tables one would obtain using different threshold values and the corresponding accuracy measures in the compact column view for the RER overvaluation at h=1m fixed horizon.

Table 4. Accuracy statistics for the RER overvaluation (h=1m)[39]

T	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	ACC	Prec	G
73	45	4459	31	1685	0.59	0.73	0.27	0.32	0.46	0.72	0.026	0.12
77	37	4701	39	1443	0.49	0.77	0.23	0.25	0.48	0.76	0.025	0.11
80	32	4883	44	1261	0.42	0.79	0.21	0.22	0.49	0.79	0.025	0.10
83	30	5065	46	1079	0.39	0.82	0.18	0.22	0.44	0.82	0.027	0.10
86	26	5248	50	896	0.34	0.85	0.15	0.20	0.43	0.85	0.028	0.10
89	23	5432	53	712	0.30	0.88	0.12	0.19	0.38	0.88	0.031	0.10

One can see that a gradual increase of the threshold t used in the forecasting rule leads to a decline of the total number of crisis signals issued, which implies lower false alarm rate at the cost of lower number of correctly identified crisis episodes. This leads to an increase in the rate of correctly identified non-crisis periods (TNR), which prevail the sample, and therefore increases the accuracy ratio. The dependence of the precision, NSR, and the J-index on the t value is a non-linear.

Table 5 below presents the contingency tables and resulted accuracy statistics for the 16 combinations of 4 indicators and 4 fixed forecast horizons with a proved predictive value. Look, for example, at the deviation of the RER from the time trend. The ROC analysis and the maximum J-index imply that we would have issued a signal about the crisis in the next period whenever the RER reaches 73rd percentile. In this case, we would correctly predict 45 crisis episodes and would miss 31 crisis episodes issuing 1685 false alarms. The minimum NSR implies that we would issue a crisis signal only when RER reaches its 95th percentile. In that case, we would correctly predict only 12 crisis episodes and would miss 64 crisis episodes issuing only 359 false alarms. However, the precision would be higher when one uses the NSR-optimal threshold (3.1%) compared to 2.6% when one uses the ROC-optimal threshold: from all the crisis signals sent, only 3.1% (2.6%) of them would be correct, and the rest 97% of signal would be

[39] Table A2 in Appendix presents the accuracy statistics for the RER at h=3, 6, and 9m ahead at the wide variety of thresholds bounded by the ROC and NSR optimal values.

false.

Table 5. Accuracy statistics for each individual indicator-horizon pair (training sample)

EWI	H	t[40]	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	ACC	Prec	G
RER overvaluation		73	45	4459	31	1685	0.59	0.73	0.27	0.32	0.46	0.72	0.026	0.12
	1	89	23	5432	53	712	0.30	0.88	0.12	0.19	0.38	0.88	0.031	0.10
		67	48	4086	27	2019	0.64	0.67	0.33	0.31	0.52	0.67	0.023	0.12
	3	87	25	5300	50	805	0.33	0.87	0.13	0.20	0.40	0.86	0.030	0.10
		55	53	3337	21	2709	0.72	0.55	0.45	0.27	0.63	0.55	0.019	0.12
	6	84	27	5104	47	942	0.36	0.84	0.16	0.21	0.43	0.84	0.028	0.10
		75	38	4596	36	1450	0.51	0.76	0.24	0.27	0.47	0.76	0.026	0.12
	9	90	17	5472	57	574	0.23	0.91	0.10	0.14	0.41	0.90	0.029	0.08
Foreign reserves		83	39	4847	34	1034	0.53	0.82	0.18	0.36	0.33	0.82	0.036	0.14
	1	90	28	5252	45	629	0.38	0.89	0.11	0.28	0.28	0.89	0.043	0.13
		64	49	3700	24	2141	0.67	0.63	0.37	0.30	0.55	0.63	0.022	0.12
	3	89	24	5151	49	690	0.33	0.88	0.12	0.21	0.36	0.88	0.034	0.11
		80	29	4580	43	1202	0.40	0.79	0.21	0.19	0.52	0.79	0.024	0.10
	6	88	21	5031	51	751	0.29	0.87	0.13	0.16	0.45	0.86	0.027	0.09
		53	47	3029	25	2753	0.65	0.52	0.48	0.18	0.73	0.53	0.017	0.11
	9	80	24	4578	48	1204	0.33	0.79	0.21	0.13	0.62	0.79	0.020	0.08
IM2/reserves	1	78	41	4427	31	1293	0.57	0.77	0.23	0.34	0.40	0.77	0.031	0.13
		90	27	5108	45	612	0.38	0.89	0.11	0.27	0.29	0.89	0.042	0.13
	3	52	56	2924	17	2756	0.77	0.51	0.49	0.28	0.63	0.52	0.020	0.12
		89	21	5006	52	674	0.29	0.88	0.12	0.17	0.41	0.87	0.030	0.09
	6	73	34	4058	38	1563	0.47	0.72	0.28	0.19	0.59	0.72	0.021	0.10
		89	17	4946	55	675	0.24	0.88	0.12	0.12	0.51	0.87	0.025	0.08
	9	64	39	3559	33	2062	0.54	0.63	0.37	0.17	0.69	0.63	0.019	0.10
		87	18	4839	54	782	0.25	0.86	0.14	0.11	0.55	0.85	0.023	0.08
Exports	1	77	35	4422	38	1378	0.48	0.76	0.24	0.24	0.50	0.76	0.025	0.11
		90	22	5175	51	625	0.30	0.89	0.11	0.19	0.36	0.88	0.034	0.10
	3	59	45	3346	28	2414	0.62	0.58	0.42	0.20	0.68	0.58	0.018	0.11
		90	19	5133	54	627	0.26	0.89	0.11	0.15	0.42	0.88	0.029	0.09
	6	57	46	3184	26	2517	0.64	0.56	0.44	0.20	0.69	0.56	0.018	0.11
		86	20	4842	52	859	0.28	0.85	0.15	0.13	0.54	0.84	0.023	0.08
	9	67	39	3733	33	1968	0.54	0.65	0.35	0.20	0.64	0.65	0.019	0.10

[40] The 1st and 2nd rows at each indicator-horizon pair indicates the ROC (NSR) optimal thresholds.

		88	20	4950	52	751	0.28	0.87	0.13	0.15	0.47	0.86	0.026	0.09

This is a feature common to predicting a subject which occurs rarely. Low recall rate can be unpleasant for the forecasters, but should not deter them from the objective to maximize the utility function of the forecast user. And the forecast user would prefer to avoid the costs of the missed crisis events, even at the 0.5% lower precision rate. Also, note that choosing a very high threshold maximizes the number of correctly predicted non-crisis episodes, which are not useful to the forecast users. The NSR-optimal threshold produced significantly lower number of correctly predicted crisis periods (17-28) than the ROC criteria (29-56). At the same time, the ROC-optimal threshold never yielded a lower G-score: it was higher than G under the NSR-optimal t for 15 out of 16 indicator-horizon pairs, and equal in one occurrence. Among all indicator-horizon pairs, one would predict the most number of crisis periods if used the M2/reserves ratio at h=3m fixed horizon. In this case the forecast would correctly identify 56 crisis periods and miss 17 crisis periods[41].

Fig. 6 below presents the modified ROC curves - the PR curves - for each indicator with good classifying properties across the selected fixed forecast horizons.

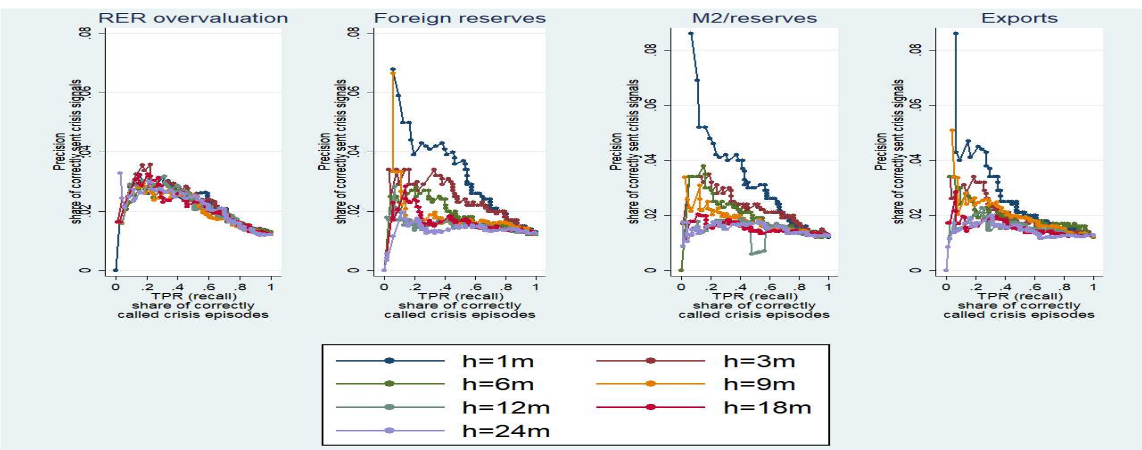

Figure 6. PR curves for each indicator with good classifying properties across horizons

Overall, these PR curves draw attention to the fact that only a small portion of all crisis signals is correctly sent. The average precision across all four indicators and horizons was around 2%, with the maximum precision of 8.6% achieved by the M2/reserves and exports at h=1m horizon. The RER overvaluation, produced almost identical PR curves across the forecast horizons. The other three indicators show that the crisis signals are more accurate at shorter horizons, with the highest accuracy 1 month before the crisis.

Another way to analyze the PR curves is by looking at each horizon across all 4 indicators. The focus is only at short fixed forecast horizons (h=1, 3, 6 and 9m).

[41] There is no data for 3 crisis episodes for this indicator-horizon pair.

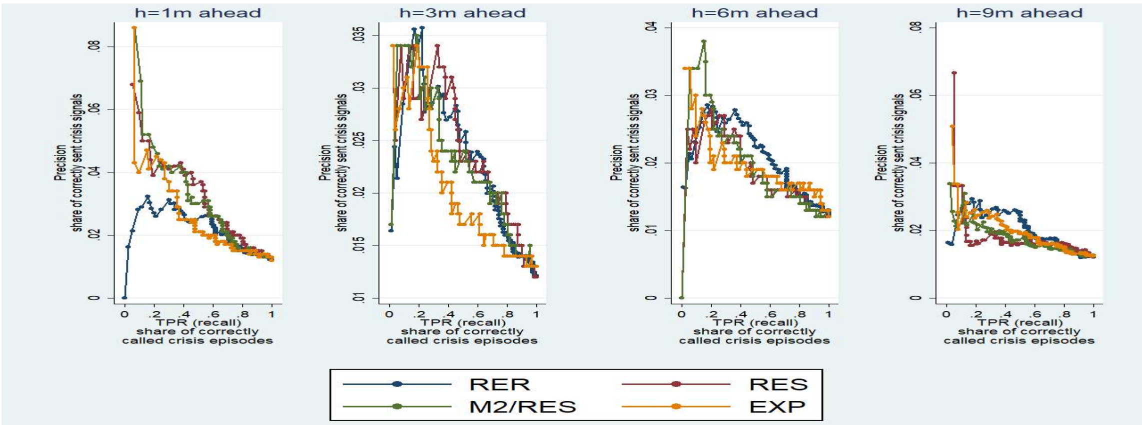

Figure 7. PR curves across indicators with good classifying properties (h=1-9m)

Figure 7 above shows that at h=1m and 3m horizons the decline in foreign reserves and increase in the M2/reserves ratio produced higher precision almost at all recall values. When forecasting a crisis event at h=6m horizon, the RER overvaluation yielded higher precision at smaller thresholds (when the TPR values are high), while the increase in M2/reserves ratio. When the crisis event is forecast 9m ahead, the decline in foreign reserves was more precise at the extreme threshold values on both ends, while the RER overvaluation – mostly in the middle range. In general, increasing the threshold raised the share of correctly called crisis signals for all indicators except the RER overvaluation. The maximum precision achieved in this sample was 8.6% at h=1m.

The in-sample precision achieved in this study seems too low. This is due to a low observed unconditional probability of the crisis events. One can show that the in-sample share of all crisis signals sent correctly is bounded between 1.22 and 55%[42]. Table A7 in the Appendix presents the formula and the resulted non-linear correspondence between the NSR and precision of correctly sent crisis signal in the given sample. For example, precision of 8.6% is achieved when the NSR fells to 0.13. Only an indicator with the NSR<=0.12 would be able to achieve a higher precision, which would come at the cost of many missed crisis events.

4.3. Out-of-sample ability to predict crisis episodes as events: modified ROC curves

Table 6 below presents the accuracy statistics for the test sample (1996-2002).

Table 6. Accuracy statistics for each individual indicator-horizon pair (test sample)

EWI	h	T	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	ACC	Prec	G
RER overvaluation	1	73	21	182	2	1415	0.91	0.11	0.89	0.03	0.97	0.13	0.015	0.12
		89	18	488	5	1109	0.78	0.31	0.69	0.09	0.89	0.31	0.016	0.11
	3	67	22	142	1	1455	0.96	0.09	0.91	0.05	0.95	0.10	0.015	0.12
		87	19	440	4	1157	0.83	0.28	0.72	0.10	0.88	0.28	0.016	0.12

[42] One can derive the relationship between the unconditional probabilities of the crisis and non-crisis periods, the NSR, and the precision using the Bayes formula (see, i.e. Krzanovwski, p.10)

	6	55	22	97	1	1500	0.96	0.06	0.94	0.02	0.98	0.07	0.014	0.12
		84	19	360	4	1237	0.83	0.23	0.77	0.05	0.94	0.23	0.015	0.11
	9	75	23	200	0	1397	1.00	0.13	0.87	0.13	0.87	0.14	0.016	0.13
		90	19	492	4	1105	0.83	0.31	0.69	0.13	0.84	0.32	0.017	0.12
Foreign reserves	1	83	9	1380	14	217	0.39	0.86	0.14	0.26	0.35	0.86	0.040	0.12
		90	3	1488	20	109	0.13	0.93	0.07	0.06	0.52	0.92	0.027	0.06
	3	64	15	844	8	753	0.65	0.53	0.47	0.18	0.72	0.53	0.020	0.11
		89	3	1439	20	158	0.13	0.90	0.10	0.03	0.76	0.89	0.019	0.05
	6	80	5	1248	18	349	0.22	0.78	0.22	0.00	1.01	0.77	0.014	0.06
		88	3	1383	20	214	0.13	0.87	0.13	0.00	1.03	0.86	0.014	0.04
	9	53	12	501	11	1096	0.52	0.31	0.69	-0.16	1.32	0.32	0.011	0.08
		80	5	1203	18	394	0.22	0.75	0.25	-0.03	1.13	0.75	0.013	0.05
IM2/reserves	1	78	6	1390	17	185	0.26	0.88	0.12	0.14	0.45	0.87	0.031	0.09
		90	1	1525	22	50	0.04	0.97	0.03	0.01	0.73	0.95	0.020	0.03
	3	52	14	802	9	773	0.61	0.51	0.49	0.12	0.81	0.51	0.018	0.10
		89	1	1478	22	97	0.04	0.94	0.06	-0.02	1.42	0.93	0.010	0.02
	6	73	4	1234	19	341	0.17	0.78	0.22	-0.04	1.24	0.77	0.012	0.04
		89	0	1424	23	151	0.00	0.90	0.10	-0.10	-	0.89	0.000	0.00
	9	64	9	1028	14	547	0.39	0.65	0.35	0.04	0.89	0.65	0.016	0.08
		87	0	1363	23	212	0.00	0.87	0.13	-0.13	-	0.85	0.000	0.00
Exports	1	77	9	1116	14	481	0.39	0.70	0.30	0.09	0.77	0.69	0.018	0.08
		90	5	1389	18	208	0.22	0.87	0.13	0.09	0.60	0.86	0.023	0.07
	3	59	16	644	7	953	0.70	0.40	0.60	0.10	0.86	0.41	0.017	0.11
		90	5	1355	18	242	0.22	0.85	0.15	0.07	0.70	0.84	0.020	0.07
	6	57	17	554	6	1043	0.74	0.35	0.65	0.09	0.88	0.35	0.016	0.11
		86	5	1245	18	352	0.22	0.78	0.22	0.00	1.01	0.77	0.014	0.06
	9	67	12	742	11	855	0.52	0.46	0.54	-0.01	1.03	0.47	0.014	0.08
		88	3	1223	20	374	0.13	0.77	0.23	-0.10	1.80	0.76	0.008	0.03

With the ROC-optimal thresholds, the RER overvaluation achieved the highest accuracy result correctly predicting all 23 crisis episodes in the test sample (at h=9m fixed horizon). Exports came in second, with 17 correctly predicted crisis episodes at h=6m fixed horizon. Foreign reserves and M2/reserves correctly identified 15 and 14 crisis episodes respectively at h=3m horizon. It is interesting to note, that the accuracy results are better 3 months before the crisis than just one month ahead. Using the NSR optimality criterion, one would identify much smaller number of crisis episodes (18-19 for RER overvaluation, 3-5 for decline in foreign reserves, 0-1 for M2/reserves, and 3-5 for decline in exports). Precision is still low, from 1.6 to 3.1.%.

4.4. Forecast combinations

The currency crisis come in different varieties, originating from different vulnerabilities and through different propagation mechanisms. Therefore, combining information sent from different indicators at the same horizon should improve the forecast accuracy.

Table 7. Accuracy statistics for combinations of 4 indicators per horizon (training sample)

H	t[43]	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	Acc	Prec	G
Rule 1-I: "At-Least-One-Indicator"													
1	ROC	69	2463	7	3681	0.91	0.40	0.60	0.31	0.66	0.41	0.018	0.13
	NSR	57	3968	19	2176	0.75	0.65	0.35	0.40	0.47	0.65	0.026	0.14
3	ROC	74	1119	1	4986	0.99	0.18	0.82	0.17	0.83	0.19	0.015	0.12
	NSR	50	3830	25	2275	0.67	0.63	0.37	0.29	0.56	0.63	0.022	0.12
6	ROC	68	1233	6	4813	0.92	0.20	0.80	0.12	0.87	0.21	0.014	0.11
	NSR	50	3515	24	2531	0.68	0.58	0.42	0.26	0.62	0.58	0.019	0.11
9	ROC	67	1528	6	4459	0.92	0.26	0.74	0.17	0.81	0.26	0.015	0.12
	NSR	45	3500	28	2487	0.62	0.58	0.42	0.20	0.67	0.58	0.018	0.10
Rule 2-I: "At-Least-Two-Indicators"													
1	ROC	51	4426	25	1718	0.67	0.72	0.28	0.39	0.42	0.72	0.029	0.14
	NSR	30	5216	46	928	0.39	0.85	0.15	0.24	0.38	0.84	0.031	0.11
3	ROC	65	2923	10	3182	0.87	0.48	0.52	0.35	0.60	0.48	0.020	0.13
	NSR	31	5098	44	1007	0.41	0.84	0.16	0.25	0.40	0.83	0.030	0.11
6	ROC	55	3503	19	2543	0.74	0.58	0.42	0.32	0.57	0.58	0.021	0.13
	NSR	25	4971	49	1075	0.34	0.82	0.18	0.16	0.53	0.82	0.023	0.09
9	ROC	53	3092	20	2895	0.73	0.52	0.48	0.24	0.67	0.52	0.018	0.11
	NSR	24	4769	49	1218	0.33	0.80	0.20	0.13	0.62	0.79	0.019	0.08

Table 7 above presents results for the forecast combinations for rules 1-I and 2-I, which combine information from the four indicators with the in- and out-of-sample predictive value, all for the test sample. The top panel shows that a rule 1-I would correctly predict 67-74 crisis episodes (with a precision of the crisis signals 1.4-1.8%) when using the ROC-t values, and only 45-57 crisis episodes (with a precision of the crisis signals 1.8-2.6%). For example, if one issued a crisis signal every time when at least one indicator

[43] This and following tables use the thresholds optimal at ROC and NSR criteria as listed in Table 17.

warned about an oncoming crisis period 1 month ahead, there would be 69 (57) correctly identified crisis episodes; and the precision would equal 1.8% (2.6%) for the ROC (NSR) t-values respectively. The ROC-threshold could achieve 99% recall and warn about 74 crisis episodes if combined information from all signals sent 3 months in advance. The NSR threshold yielded the highest recall (75%) 1 month before a crisis occurs. Rule 2-I reduced the number of false alarms, increasing the precision of a signal to 1.8–2.9% (1.9-3.1%) for the ROC (NSR) thresholds respectively. However, the number of correctly identified crisis periods reduced to 51-65 (24-31) for the ROC (NSR) optimal t values. The ROC-t yielded the G scores which were at least as good as those from the NSR-t at all horizon, with the exception of h=1m ahead.

The same crisis could be signaled during the 9m window only once (i.e. 1, 3, 6, or 9m ahead), or several times (if a signal was persistent). Table 21 below presents the accuracy of the forecasts obtained when information from the same indicator is combined at different horizons. It shows that deviation of the RER from the trend alone could correctly predict 57 (36) crisis periods if one used a rule 1-H (when a RER issued a signal at least at one of 4 forecast horizons) with the ROC (NSR) thresholds. Limiting signals to the case when an indicator issued warning at least at 2 of 4 forecast horizons and using the rule 2-I, the RER overvaluation would help predicting 53 (25) crisis periods with ROC (NSR) optimal values respectively. The precision of a crisis signal would equal 1.9 (2.3%) and 2.8% (2.6%) when the rule 1-H (2-H) was used with the ROC and NSR optimal thresholds respectively. Rule 1-H would predict the highest number of crisis periods when M2/reserves ratio used with the ROC threshold or exports with the NSR threshold. Rule 2-H would favor using exports alone, as it predicted no worse (better) with the ROC (NSR) thresholds.

Table 8. Accuracy statistics for combinations of 4 horizons per indicator (training sample)

Indicator	T	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	Acc	Prec	G
Rule 1-H: “At-Least-One-Horizon”													
RER	ROC	57	3141	19	3003	0.75	0.51	0.49	0.26	0.65	0.51	0.019	0.12
	NSR	36	4911	40	1233	0.47	0.80	0.20	0.27	0.42	0.80	0.028	0.12
Foreign reserves	ROC	59	2411	14	3480	0.81	0.41	0.59	0.22	0.73	0.41	0.017	0.12
	NSR	38	4086	35	1805	0.52	0.69	0.31	0.21	0.59	0.69	0.021	0.10
M2 to reserves	ROC	65	2110	8	3708	0.89	0.36	0.64	0.25	0.72	0.37	0.017	0.12
	NSR	39	4152	35	1666	0.53	0.71	0.29	0.24	0.54	0.71	0.023	0.11
Exports	ROC	64	1871	9	3943	0.88	0.32	0.68	0.20	0.77	0.33	0.016	0.12
	NSR	45	1871	28	1947	0.62	0.49	0.51	0.11	0.83	0.49	0.023	0.12
Rule 2-H: “At-Least-Two-Horizons”													
RER	ROC	53	3867	23	2277	0.70	0.63	0.37	0.33	0.53	0.63	0.023	0.13
	NSR	25	5211	51	933	0.33	0.85	0.15	0.18	0.46	0.84	0.026	0.09
Foreign reserves	ROC	51	3730	22	2161	0.70	0.63	0.37	0.33	0.53	0.63	0.023	0.13
	NSR	29	4878	44	1013	0.40	0.83	0.17	0.23	0.43	0.82	0.028	0.11

M2 to reserves	ROC	50	3351	23	2467	0.68	0.58	0.42	0.26	0.62	0.58	0.020	0.12
	NSR	28	4824	46	994	0.38	0.83	0.17	0.21	0.45	0.82	0.027	0.10
Exports	ROC	53	3155	20	2659	0.73	0.54	0.46	0.27	0.63	0.54	0.020	0.12
	NSR	27	2935	46	883	0.37	0.77	0.23	0.14	0.63	0.76	0.030	0.10

Overall, each indicator used individually in rule 1-H (2-H) would correctly point to 57-65 (50-53) crisis months when signals were issued with the ROC-optimal threshold values, and only 36-45 (25-28) crisis months with the NSR-optimal thresholds.

5. Conclusion

This chapter contributes to the literature on the design and evaluation of the signal approach to construct an Early Warning System (EWS) of the currency crisis episodes. It re-examines predictive value of the eight Early Earning Indicators of currency crisis which were found to have predictive value by Kaminsky and Reinhart (1999). It uses monthly data from 20 countries over a span of 26 years (1970-1995). All the indicators are calculated as percentages, and then sorted into 1-100 percentiles. These percentiles are used in the forecasting rule to predict crisis. I use the analysis of the ROC curves to test whether an indicator has distinctly different behavior in times of crisis and tranquility.

Then I employ the in-sample and out-of-sample criteria of predictive value as established in the first chapter to determine a list of indicators which take on significantly different values in two regimes (crisis vs. tranquility), and therefore can be used as classifiers to distinguish between the two states. Only the deviation of the RER from a trend, the foreign reserves, the ratio of broad money M2 to reserves, and decline in exports have demonstrated both in-sample and out-of-sample predictive value[44].

I also employed a novel way to construct the convex hull ROC curves to explain that the previous literature used more liberal criteria and therefore found more indicators had predictive value. Then, I explained how to choose an optimal threshold using the ROC-implied criteria, and how this choice differs from the minimizing noise-to-signal ratio previously used in the literature. In general, thresholds chosen in accordance with the maximum J-index in the ROC curves analysis result in the higher rate of correctly called crisis episodes.

I also employed the modified ROC curves to show the relationship between the precision of sent signals and recall of crisis episodes. Then, I analyzed the accuracy statistics to illustrate how the accuracy statistics, in particular, the tradeoff between the recall and precision depends on choice of the threshold used in the forecasting rule. Results show that although the identified EWIs do perform better than a random guess, they have very weak predictive value. In general, they identify no more 2/3 of crisis episodes, generating hundreds false alarms. Precision of the signals sent does not exceed 8.5%. It means that for every

[44] The RER had in-sample and out-of-sample predictive value at all horizons, while the other three indicators were valuable only at h=6m and shorter.

correctly sent crisis signal there are a dozen of false ones.

Finally, I exploited the benefits of forecast combinations using several ad-hoc rules and found that they help one to improve the accuracy of results, including both recall and precision.

To conclude, the alternative method to evaluate the leading indicators of currency crisis yields more conservative conclusions because it evaluates signals at the fixed forecast horizons instead of using the 24 months forecast window.

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Appendix

Figure A1. ROC curves for EWI with the out-of-sample value (h=3, 6, 9 m)

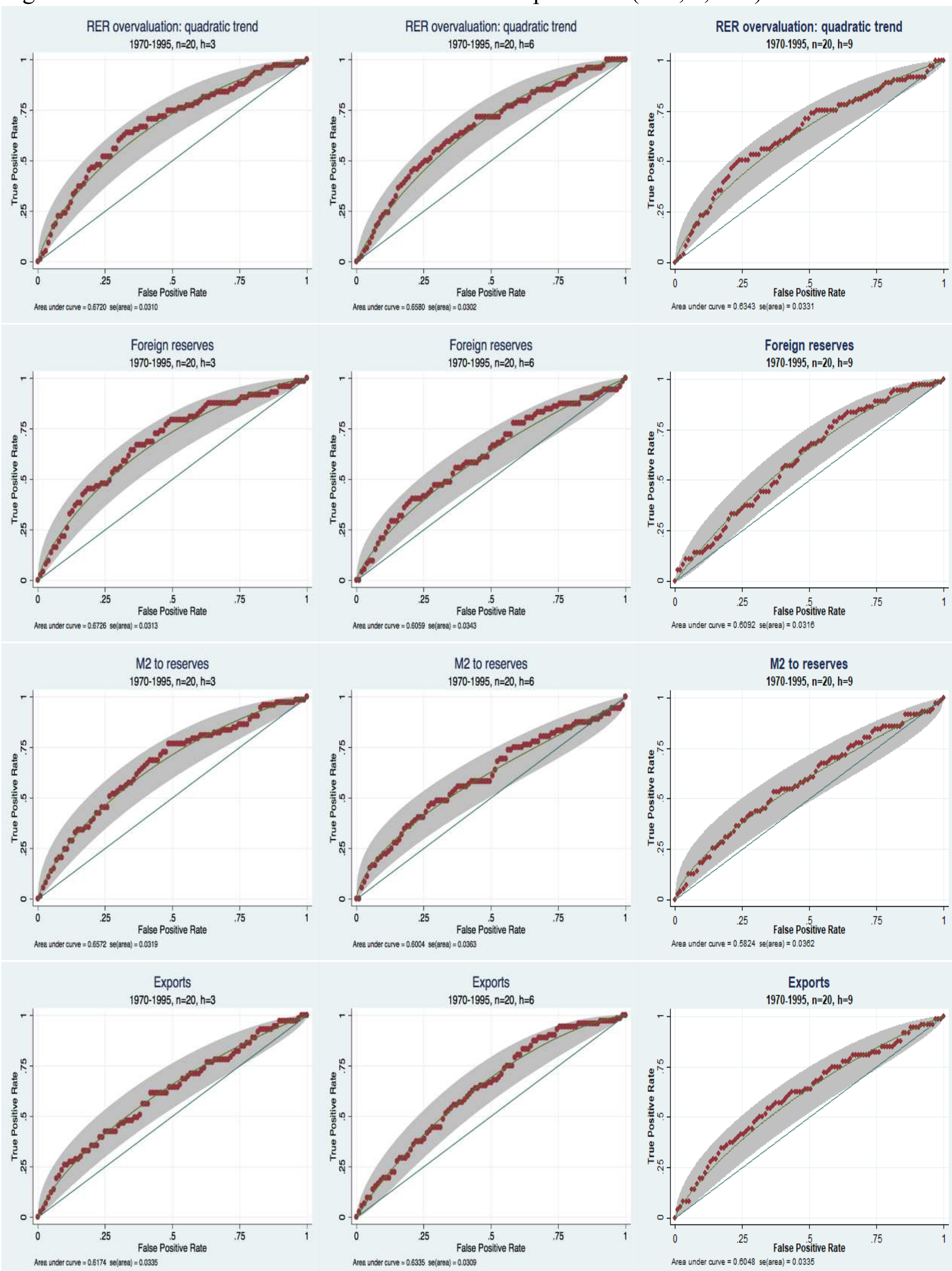

Figure A2. ROC curves for EWI with the out-of-sample value (h=12, 18, 24 m)

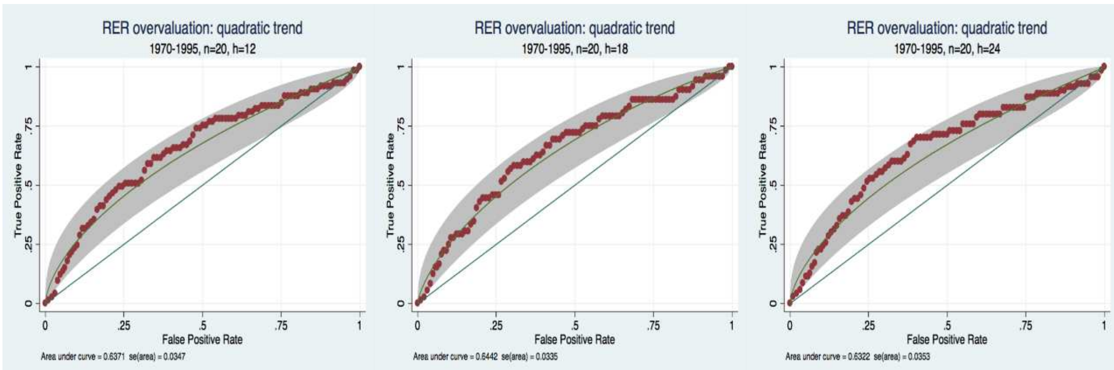

Figure A3. Indicators with in-sample value not significant out-of-sample

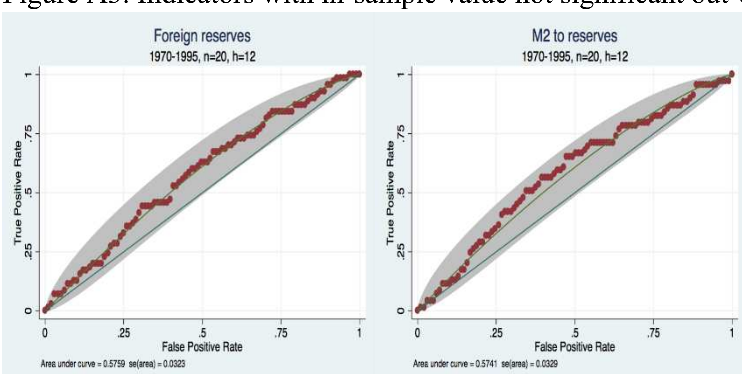

Figure A4. Precision-recall curves for R deviation at h=12, 18, and 24m.

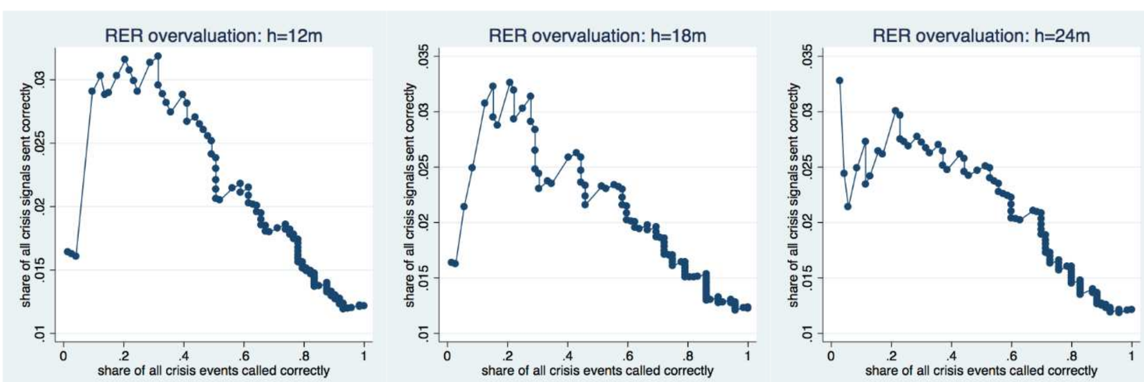

Table A1. Dates of identified currency crisis episodes in the training and test sets

Country	Training set	Test set
Argentina	1970m6, 1975m6, 1981m2, 1982m7, 1986m9, 1989m4, 1990m2	2002m1
Bolivia	1982m11, 1983m11, 1985m9	None
Brazil	1983m2, 1986m11, 1989m7, 1990m11, 1991m10	1999m1
Chile	1971m12, 1972m8, 1973m10, 1974m12, 1976m1, 1982m8, 1984m9	None
Colombia	1983m3, 1985m2	1997m9, 1998m9, 1999m8, 2002m7
Denmark	1971m5, 1973m6, 1979m11, 1993m8	2003m6
Finland	1973m6, 1982m10, 1991m11, 1992m9	Dropped the sample as a EMU member
Indonesia	1978m11, 1983m4, 1986m9	1997m12, 1998m6
Israel	1974m11, 1977m11, 1983m10, 1984m7	None
Malaysia	1975m7	1997m8, 1998m6
Mexico	1976m9, 1982m2, 1982m12, 1994m12	None
Norway	1973m6, 1978m2, 1986m5, 1992m12	1998m1, 1999m7, 2000m11, 2003m2
Peru	1976m6, 1987m10	None
Philippines	1970m2, 1983m10, 1984m6, 1986m2	1997m12
Spain	1976m2, 1977m7, 1982m12, 1992m9, 1993m5	Dropped the sample as a EMU member
Sweden	1977m8, 1981m9, 1982m10, 1992m11	None
Thailand	1978m11, 1981m7, 1984m11	1997m7, 1998m6, 1999m9, 2000m7
Turkey	1970m8, 1980m1, 1994m3	2001m2
Uruguay	1971m12, 1982m10	2002m7
Venezuela	1984m2, 1986m12, 1989m3, 1994m5, 1995m12	2002m2
Total	76	23

Table A2. Relationship between the NSR and precision in the given training sample[45]

NSR	Precision
0.01	0.55
0.02	0.38
0.03	0.29
0.04	0.24
0.05-0.06	0.20-0.17
0.07-0.11	0.15-0.10
0.12-0.15	0.09-0.08
0.16-0.19	0.07-0.06
0.2-0.26	0.05
0.27-0.34	0.04
0.35-0.48	0.03
0.49-0.81	0.02
0.82-1.0	0.012-0.014

[45] Using the Bayes theorem and notations accepted in this chapter, we can express precision as following:

$$Precision = \frac{TPR * p(Y=1)}{TPR * p(Y=1) + FPR * p(Y=0)}$$

After a simple algebraic transformation, one can rewrite this as:

$$Precision = 1: \left[1 + \frac{FPR * p(Y=0)}{TPR * p(Y=1)}\right] = \frac{1}{1 + NSR\frac{p(Y=0)}{p(Y=1)}}$$

In the given training sample, we had $p(Y=1) = 1.22\%$ and $p(Y=0) = 98.78\%$ respectively. These numbers were used to calculate the correspondence between the NSR (with 0.01 step) and the resulted precision, which are grouped in the table A3 above.

Table A3. Accuracy statistics for the number of indicator-horizon pairs

T	TP	TN	FN	FP	TPR	TNR	FPR	J	NSR	AC	Precision
RER overvaluation, h=3m											
67	48	4086	27	2019	0.64	0.67	0.33	0.31	0.52	0.67	0.023
68	47	4147	28	1958	0.63	0.68	0.32	0.31	0.51	0.68	0.023
69	46	4208	29	1897	0.61	0.69	0.31	0.30	0.51	0.69	0.024
70	45	4268	30	1837	0.60	0.70	0.30	0.30	0.50	0.70	0.024
71	42	4326	33	1779	0.56	0.71	0.29	0.27	0.52	0.71	0.023
72	42	4389	33	1716	0.56	0.72	0.28	0.28	0.50	0.72	0.024
73	39	4448	36	1657	0.52	0.73	0.27	0.25	0.52	0.73	0.023
74	39	4511	36	1594	0.52	0.74	0.26	0.26	0.50	0.74	0.024
75	39	4573	36	1532	0.52	0.75	0.25	0.27	0.48	0.75	0.025
76	39	4635	36	1470	0.52	0.76	0.24	0.28	0.46	0.76	0.026
77	36	4695	39	1410	0.48	0.77	0.23	0.25	0.48	0.77	0.025
78	36	4757	39	1348	0.48	0.78	0.22	0.26	0.46	0.78	0.026
79	35	4818	40	1287	0.47	0.79	0.21	0.26	0.45	0.79	0.026
80	35	4879	40	1226	0.47	0.80	0.20	0.27	0.43	0.80	0.028
81	34	4939	41	1166	0.45	0.81	0.19	0.26	0.42	0.80	0.028
82	31	4998	44	1107	0.41	0.82	0.18	0.23	0.44	0.81	0.027
83	29	5057	46	1048	0.39	0.83	0.17	0.22	0.44	0.82	0.027
84	28	5119	47	986	0.37	0.84	0.16	0.21	0.43	0.83	0.028
85	28	5181	47	924	0.37	0.85	0.15	0.22	0.41	0.84	0.029
86	26	5240	49	865	0.35	0.86	0.14	0.21	0.41	0.85	0.029
87	25	5300	50	805	0.33	0.87	0.13	0.20	0.40	0.86	0.030
RER overvaluation, h=6m											
55	53	3337	21	2709	0.72	0.55	0.45	0.27	0.63	0.55	0.019
56	50	3396	24	2650	0.68	0.56	0.44	0.24	0.65	0.56	0.019
57	49	3458	25	2588	0.66	0.57	0.43	0.23	0.65	0.57	0.019
58	49	3520	25	2526	0.66	0.58	0.42	0.24	0.63	0.58	0.019
59	48	3582	26	2464	0.65	0.59	0.41	0.24	0.63	0.59	0.019
60	47	3643	27	2403	0.64	0.60	0.40	0.24	0.63	0.60	0.019
61	47	3705	27	2341	0.64	0.61	0.39	0.25	0.61	0.61	0.020
62	46	3767	28	2279	0.62	0.62	0.38	0.24	0.61	0.62	0.020
63	46	3829	28	2217	0.62	0.63	0.37	0.25	0.59	0.63	0.020
64	45	3891	29	2155	0.61	0.64	0.36	0.25	0.59	0.64	0.020
65	44	3952	30	2094	0.59	0.65	0.35	0.25	0.58	0.65	0.021
66	44	4014	30	2032	0.59	0.66	0.34	0.26	0.57	0.66	0.021
67	43	4076	31	1970	0.58	0.67	0.33	0.26	0.56	0.67	0.021
68	42	4136	32	1910	0.57	0.68	0.32	0.25	0.56	0.68	0.022
69	41	4196	33	1850	0.55	0.69	0.31	0.25	0.55	0.69	0.022
70	41	4257	33	1789	0.55	0.70	0.30	0.26	0.53	0.70	0.022
71	40	4317	34	1729	0.54	0.71	0.29	0.25	0.53	0.71	0.023
72	38	4377	36	1669	0.51	0.72	0.28	0.24	0.54	0.72	0.022
73	37	4437	37	1609	0.50	0.73	0.27	0.23	0.53	0.73	0.022
74	37	4500	37	1546	0.50	0.74	0.26	0.24	0.51	0.74	0.023
75	36	4561	38	1485	0.49	0.75	0.25	0.24	0.50	0.75	0.024
76	35	4622	39	1424	0.47	0.76	0.24	0.24	0.50	0.76	0.024

77	34	4684	40	1362	0.46	0.77	0.23	0.23	0.49	0.77	0.024
78	34	4745	40	1301	0.46	0.78	0.22	0.24	0.47	0.78	0.025
79	33	4806	41	1240	0.45	0.79	0.21	0.24	0.46	0.79	0.026
80	31	4864	43	1182	0.42	0.80	0.20	0.22	0.47	0.80	0.026
81	30	4924	44	1122	0.41	0.81	0.19	0.22	0.46	0.81	0.026
82	29	4983	45	1063	0.39	0.82	0.18	0.22	0.45	0.82	0.027
83	28	5043	46	1003	0.38	0.83	0.17	0.21	0.44	0.83	0.027
84	27	5104	47	942	0.36	0.84	0.16	0.21	0.43	0.84	0.028
RER overvaluation, h=9m											
75	38	4596	36	1450	0.51	0.76	0.24	0.27	0.47	0.76	0.026
76	36	4657	38	1389	0.49	0.77	0.23	0.26	0.47	0.77	0.025
77	35	4720	39	1326	0.48	0.78	0.22	0.26	0.46	0.78	0.026
78	34	4779	40	1267	0.47	0.79	0.21	0.26	0.45	0.79	0.026
79	31	4839	43	1207	0.42	0.80	0.20	0.23	0.47	0.80	0.025
80	30	4899	44	1147	0.41	0.81	0.19	0.22	0.46	0.81	0.025
81	29	4957	45	1089	0.40	0.82	0.18	0.22	0.45	0.81	0.026
82	26	5015	48	1031	0.36	0.83	0.17	0.19	0.48	0.82	0.025
83	26	5076	48	970	0.36	0.84	0.16	0.20	0.45	0.83	0.026
84	25	5137	49	909	0.34	0.85	0.15	0.19	0.44	0.84	0.027
85	23	5196	51	850	0.32	0.86	0.14	0.17	0.45	0.85	0.026
86	20	5250	54	796	0.27	0.87	0.13	0.14	0.48	0.86	0.025
87	18	5308	56	738	0.25	0.88	0.12	0.12	0.50	0.87	0.024
88	18	5363	56	683	0.25	0.89	0.11	0.13	0.46	0.88	0.026
89	17	5416	57	630	0.23	0.90	0.10	0.13	0.45	0.89	0.026
90	17	5472	57	574	0.23	0.91	0.10	0.14	0.41	0.90	0.029
Foreign reserves, h=1m											
83	39	4847	34	1034	0.53	0.82	0.18	0.36	0.33	0.82	0.036
84	38	4905	35	976	0.52	0.83	0.17	0.35	0.32	0.83	0.037
85	34	4961	39	920	0.47	0.84	0.16	0.31	0.34	0.84	0.036
86	34	5020	39	861	0.47	0.85	0.15	0.32	0.31	0.85	0.038
87	33	5079	40	802	0.45	0.86	0.14	0.32	0.30	0.86	0.040
88	30	5135	43	746	0.41	0.87	0.13	0.28	0.31	0.87	0.039
89	29	5194	44	687	0.40	0.88	0.12	0.28	0.29	0.88	0.041
90	28	5252	45	629	0.38	0.89	0.11	0.28	0.28	0.89	0.043
Foreign reserves, h=3m											
64	49	3700	24	2141	0.67	0.63	0.37	0.30	0.55	0.63	0.022
65	47	3757	26	2084	0.64	0.64	0.36	0.29	0.55	0.64	0.022
66	47	3817	26	2024	0.64	0.65	0.35	0.30	0.54	0.65	0.023
67	45	3873	28	1968	0.62	0.66	0.34	0.28	0.55	0.66	0.022
68	43	3931	30	1910	0.59	0.67	0.33	0.26	0.56	0.67	0.022
69	43	3989	30	1852	0.59	0.68	0.32	0.27	0.54	0.68	0.023
70	41	4045	32	1796	0.56	0.69	0.31	0.25	0.55	0.69	0.022
71	40	4103	33	1738	0.55	0.70	0.30	0.25	0.54	0.70	0.022
72	40	4163	33	1678	0.55	0.71	0.29	0.26	0.52	0.71	0.023
73	39	4222	34	1619	0.53	0.72	0.28	0.26	0.52	0.72	0.024
74	36	4279	37	1562	0.49	0.73	0.27	0.23	0.54	0.73	0.023
75	35	4336	38	1505	0.48	0.74	0.26	0.22	0.54	0.74	0.023
76	35	4395	38	1446	0.48	0.75	0.25	0.23	0.52	0.75	0.024

77	35	4455	38	1386	0.48	0.76	0.24	0.24	0.49	0.76	0.025
78	34	4512	39	1329	0.47	0.77	0.23	0.24	0.49	0.77	0.025
79	34	4572	39	1269	0.47	0.78	0.22	0.25	0.47	0.78	0.026
80	33	4631	40	1210	0.45	0.79	0.21	0.24	0.46	0.79	0.027
81	33	4691	40	1150	0.45	0.80	0.20	0.26	0.44	0.80	0.028
82	33	4750	40	1091	0.45	0.81	0.19	0.27	0.41	0.81	0.029
83	32	4809	41	1032	0.44	0.82	0.18	0.26	0.40	0.82	0.030
84	31	4866	42	975	0.42	0.83	0.17	0.26	0.39	0.83	0.031
85	28	4919	45	922	0.38	0.84	0.16	0.23	0.41	0.84	0.029
86	28	4976	45	865	0.38	0.85	0.15	0.24	0.39	0.85	0.031
87	27	5035	46	806	0.37	0.86	0.14	0.23	0.37	0.86	0.032
88	25	5092	48	749	0.34	0.87	0.13	0.21	0.37	0.87	0.032
89	24	5151	49	690	0.33	0.88	0.12	0.21	0.36	0.88	0.034
Foreign reserves, h=6m											
80	29	4580	43	1202	0.40	0.79	0.21	0.19	0.52	0.79	0.024
81	28	4637	44	1145	0.39	0.80	0.20	0.19	0.51	0.80	0.024
82	27	4694	45	1088	0.38	0.81	0.19	0.19	0.50	0.81	0.024
83	26	4752	46	1030	0.36	0.82	0.18	0.18	0.49	0.82	0.025
84	23	4806	49	976	0.32	0.83	0.17	0.15	0.53	0.82	0.023
85	23	4861	49	921	0.32	0.84	0.16	0.16	0.50	0.83	0.024
86	21	4912	51	870	0.29	0.85	0.15	0.14	0.52	0.84	0.024
87	21	4972	51	810	0.29	0.86	0.14	0.15	0.48	0.85	0.025
88	21	5031	51	751	0.29	0.87	0.13	0.16	0.45	0.86	0.027
Foreign reserves, h=9m											
53	47	3029	25	2753	0.65	0.52	0.48	0.18	0.73	0.53	0.017
54	46	3084	26	2698	0.64	0.53	0.47	0.17	0.73	0.53	0.017
55	43	3136	29	2646	0.60	0.54	0.46	0.14	0.77	0.54	0.016
56	42	3194	30	2588	0.58	0.55	0.45	0.14	0.77	0.55	0.016
57	41	3252	31	2530	0.57	0.56	0.44	0.13	0.77	0.56	0.016
58	41	3310	31	2472	0.57	0.57	0.43	0.14	0.75	0.57	0.016
59	41	3366	31	2416	0.57	0.58	0.42	0.15	0.73	0.58	0.017
60	41	3424	31	2358	0.57	0.59	0.41	0.16	0.72	0.59	0.017
61	40	3480	32	2302	0.56	0.60	0.40	0.16	0.72	0.60	0.017
62	37	3533	35	2249	0.51	0.61	0.39	0.13	0.76	0.61	0.016
63	35	3590	37	2192	0.49	0.62	0.38	0.11	0.78	0.62	0.016
64	35	3648	37	2134	0.49	0.63	0.37	0.12	0.76	0.63	0.016
65	34	3706	38	2076	0.47	0.64	0.36	0.11	0.76	0.64	0.016
66	32	3763	40	2019	0.44	0.65	0.35	0.10	0.79	0.65	0.016
67	32	3821	40	1961	0.44	0.66	0.34	0.11	0.76	0.66	0.016
68	32	3879	40	1903	0.44	0.67	0.33	0.12	0.74	0.67	0.017
69	32	3936	40	1846	0.44	0.68	0.32	0.13	0.72	0.68	0.017
70	30	3991	42	1791	0.42	0.69	0.31	0.11	0.74	0.69	0.016
71	29	4049	43	1733	0.40	0.70	0.30	0.10	0.74	0.70	0.016
72	27	4106	45	1676	0.38	0.71	0.29	0.09	0.77	0.71	0.016
73	27	4167	45	1615	0.38	0.72	0.28	0.10	0.74	0.72	0.016
74	27	4225	45	1557	0.38	0.73	0.27	0.11	0.72	0.73	0.017
75	27	4283	45	1499	0.38	0.74	0.26	0.12	0.69	0.74	0.018
76	26	4341	46	1441	0.36	0.75	0.25	0.11	0.69	0.75	0.018

77	25	4400	47	1382	0.35	0.76	0.24	0.11	0.69	0.76	0.018
78	24	4457	48	1325	0.33	0.77	0.23	0.10	0.69	0.77	0.018
79	24	4518	48	1264	0.33	0.78	0.22	0.11	0.66	0.78	0.019
80	24	4578	48	1204	0.33	0.79	0.21	0.13	0.62	0.79	0.020
M2/reserves, h=1m											
78	41	4427	31	1293	0.57	0.77	0.23	0.34	0.40	0.77	0.031
79	39	4483	33	1237	0.54	0.78	0.22	0.33	0.40	0.78	0.031
80	36	4538	36	1182	0.50	0.79	0.21	0.29	0.41	0.79	0.030
81	35	4594	37	1126	0.49	0.80	0.20	0.29	0.41	0.80	0.030
82	33	4650	39	1070	0.46	0.81	0.19	0.27	0.41	0.81	0.030
83	33	4708	39	1012	0.46	0.82	0.18	0.28	0.39	0.82	0.032
84	31	4764	41	956	0.43	0.83	0.17	0.26	0.39	0.83	0.031
85	31	4823	41	897	0.43	0.84	0.16	0.27	0.36	0.84	0.033
86	31	4881	41	839	0.43	0.85	0.15	0.28	0.34	0.85	0.036
87	30	4937	42	783	0.42	0.86	0.14	0.28	0.33	0.86	0.037
88	30	4995	42	725	0.42	0.87	0.13	0.29	0.30	0.87	0.040
89	28	5051	44	669	0.39	0.88	0.12	0.27	0.30	0.88	0.040
90	27	5108	45	612	0.38	0.89	0.11	0.27	0.29	0.89	0.042
M2/reserves, h=3m											
52	56	2924	17	2756	0.77	0.51	0.49	0.28	0.63	0.52	0.020
53	53	2978	20	2702	0.73	0.52	0.48	0.25	0.66	0.53	0.019
54	53	3034	20	2646	0.73	0.53	0.47	0.26	0.64	0.54	0.020
55	52	3090	21	2590	0.71	0.54	0.46	0.26	0.64	0.55	0.020
56	50	3144	23	2536	0.68	0.55	0.45	0.24	0.65	0.56	0.019
57	50	3200	23	2480	0.68	0.56	0.44	0.25	0.64	0.56	0.020
58	50	3257	23	2423	0.68	0.57	0.43	0.26	0.62	0.57	0.020
59	50	3314	23	2366	0.68	0.58	0.42	0.27	0.61	0.58	0.021
60	49	3371	24	2309	0.67	0.59	0.41	0.26	0.61	0.59	0.021
61	48	3428	25	2252	0.66	0.60	0.40	0.26	0.60	0.60	0.021
62	47	3485	26	2195	0.64	0.61	0.39	0.26	0.60	0.61	0.021
63	46	3541	27	2139	0.63	0.62	0.38	0.25	0.60	0.62	0.021
64	45	3596	28	2084	0.62	0.63	0.37	0.25	0.60	0.63	0.021
65	43	3652	30	2028	0.59	0.64	0.36	0.23	0.61	0.64	0.021
66	42	3708	31	1972	0.58	0.65	0.35	0.23	0.60	0.65	0.021
67	42	3764	31	1916	0.58	0.66	0.34	0.24	0.59	0.66	0.021
68	41	3822	32	1858	0.56	0.67	0.33	0.23	0.58	0.67	0.022
69	40	3879	33	1801	0.55	0.68	0.32	0.23	0.58	0.68	0.022
70	40	3935	33	1745	0.55	0.69	0.31	0.24	0.56	0.69	0.022
71	39	3992	34	1688	0.53	0.70	0.30	0.24	0.56	0.70	0.023
72	38	4049	35	1631	0.52	0.71	0.29	0.23	0.55	0.71	0.023
73	38	4103	35	1577	0.52	0.72	0.28	0.24	0.53	0.72	0.024
74	37	4160	36	1520	0.51	0.73	0.27	0.24	0.53	0.73	0.024
75	33	4213	40	1467	0.45	0.74	0.26	0.19	0.57	0.74	0.022
76	33	4271	40	1409	0.45	0.75	0.25	0.20	0.55	0.75	0.023
77	33	4330	40	1350	0.45	0.76	0.24	0.21	0.53	0.76	0.024
78	31	4384	42	1296	0.42	0.77	0.23	0.20	0.54	0.77	0.023
79	31	4442	42	1238	0.42	0.78	0.22	0.21	0.51	0.78	0.024
80	29	4498	44	1182	0.40	0.79	0.21	0.19	0.52	0.79	0.024

81	28	4554	45	1126	0.38	0.80	0.20	0.19	0.52	0.80	0.024
82	26	4609	47	1071	0.36	0.81	0.19	0.17	0.53	0.81	0.024
83	26	4667	47	1013	0.36	0.82	0.18	0.18	0.50	0.82	0.025
84	25	4724	48	956	0.34	0.83	0.17	0.17	0.49	0.83	0.025
85	25	4782	48	898	0.34	0.84	0.16	0.18	0.46	0.84	0.027
86	25	4840	48	840	0.34	0.85	0.15	0.19	0.43	0.85	0.029
87	24	4894	49	786	0.33	0.86	0.14	0.19	0.42	0.85	0.030
88	21	4949	52	731	0.29	0.87	0.13	0.16	0.45	0.86	0.028
89	21	5006	52	674	0.29	0.88	0.12	0.17	0.41	0.87	0.030
M2/reserves, h=6m											
73	34	4058	38	1563	0.47	0.72	0.28	0.19	0.59	0.72	0.021
74	33	4115	39	1506	0.46	0.73	0.27	0.19	0.58	0.73	0.021
75	31	4168	41	1453	0.43	0.74	0.26	0.17	0.60	0.74	0.021
76	29	4224	43	1397	0.40	0.75	0.25	0.15	0.62	0.75	0.020
77	29	4282	43	1339	0.40	0.76	0.24	0.16	0.59	0.76	0.021
78	29	4338	43	1283	0.40	0.77	0.23	0.17	0.57	0.77	0.022
79	28	4395	44	1226	0.39	0.78	0.22	0.17	0.56	0.78	0.022
80	27	4452	45	1169	0.38	0.79	0.21	0.17	0.55	0.79	0.023
81	26	4507	46	1114	0.36	0.80	0.20	0.16	0.55	0.80	0.023
82	26	4563	46	1058	0.36	0.81	0.19	0.17	0.52	0.81	0.024
83	25	4618	47	1003	0.35	0.82	0.18	0.17	0.51	0.82	0.024
84	23	4673	49	948	0.32	0.83	0.17	0.15	0.53	0.82	0.024
85	21	4728	51	893	0.29	0.84	0.16	0.13	0.54	0.83	0.023
86	20	4783	52	838	0.28	0.85	0.15	0.13	0.54	0.84	0.023
87	20	4836	52	785	0.28	0.86	0.14	0.14	0.50	0.85	0.025
88	18	4891	54	730	0.25	0.87	0.13	0.12	0.52	0.86	0.024
89	17	4946	55	675	0.24	0.88	0.12	0.12	0.51	0.87	0.025
M2/reserves, h=9m											
64	39	3559	33	2062	0.54	0.63	0.37	0.17	0.69	0.63	0.019
65	35	3614	37	2007	0.49	0.64	0.36	0.14	0.72	0.64	0.017
66	34	3669	38	1952	0.48	0.65	0.35	0.13	0.72	0.65	0.017
67	32	3724	40	1897	0.45	0.66	0.34	0.11	0.75	0.66	0.017
68	32	3782	40	1839	0.45	0.67	0.33	0.12	0.73	0.67	0.017
69	31	3836	41	1785	0.44	0.68	0.32	0.12	0.73	0.68	0.017
70	31	3891	41	1730	0.44	0.69	0.31	0.13	0.70	0.69	0.018
71	31	3947	41	1674	0.44	0.70	0.30	0.14	0.68	0.70	0.018
72	30	4004	42	1617	0.42	0.71	0.29	0.13	0.68	0.71	0.018
73	30	4057	42	1564	0.42	0.72	0.28	0.14	0.66	0.72	0.019
74	29	4114	43	1507	0.41	0.73	0.27	0.14	0.66	0.73	0.019
75	28	4169	44	1452	0.39	0.74	0.26	0.14	0.66	0.74	0.019
76	28	4228	44	1393	0.39	0.75	0.25	0.15	0.63	0.75	0.020
77	26	4284	46	1337	0.37	0.76	0.24	0.13	0.65	0.76	0.019
78	26	4341	46	1280	0.37	0.77	0.23	0.14	0.62	0.77	0.020
79	24	4396	48	1225	0.34	0.78	0.22	0.12	0.64	0.78	0.019
80	23	4454	49	1167	0.32	0.79	0.21	0.12	0.64	0.79	0.019
81	22	4509	50	1112	0.31	0.80	0.20	0.11	0.64	0.80	0.019
82	22	4566	50	1055	0.31	0.81	0.19	0.12	0.61	0.81	0.020
83	20	4619	52	1002	0.28	0.82	0.18	0.10	0.63	0.82	0.020

84	20	4677	52	944	0.28	0.83	0.17	0.11	0.60	0.83	0.021
85	19	4733	53	888	0.27	0.84	0.16	0.11	0.59	0.83	0.021
86	18	4786	54	835	0.25	0.85	0.15	0.11	0.59	0.84	0.021
87	18	4839	54	782	0.25	0.86	0.14	0.11	0.55	0.85	0.023
Exports, h=1m											
77	35	4422	38	1378	0.48	0.76	0.24	0.24	0.50	0.76	0.025
78	33	4479	40	1321	0.45	0.77	0.23	0.22	0.50	0.77	0.024
79	33	4538	40	1262	0.45	0.78	0.22	0.23	0.48	0.78	0.025
80	31	4595	42	1205	0.42	0.79	0.21	0.22	0.49	0.79	0.025
81	29	4652	44	1148	0.40	0.80	0.20	0.20	0.50	0.80	0.025
82	28	4710	45	1090	0.38	0.81	0.19	0.20	0.49	0.81	0.025
83	27	4768	46	1032	0.37	0.82	0.18	0.19	0.48	0.82	0.025
84	27	4827	46	973	0.37	0.83	0.17	0.20	0.45	0.83	0.027
85	27	4886	46	914	0.37	0.84	0.16	0.21	0.43	0.84	0.029
86	26	4944	47	856	0.36	0.85	0.15	0.21	0.41	0.85	0.029
87	26	5002	47	798	0.36	0.86	0.14	0.22	0.39	0.86	0.032
88	26	5061	47	739	0.36	0.87	0.13	0.23	0.36	0.87	0.034
89	24	5118	49	682	0.33	0.88	0.12	0.21	0.36	0.88	0.034
90	22	5175	51	625	0.30	0.89	0.11	0.19	0.36	0.88	0.034
Exports, h=3m											
59	45	3346	28	2414	0.62	0.58	0.42	0.20	0.68	0.58	0.018
60	41	3401	32	2359	0.56	0.59	0.41	0.15	0.73	0.59	0.017
61	41	3458	32	2302	0.56	0.60	0.40	0.16	0.71	0.60	0.017
62	41	3517	32	2243	0.56	0.61	0.39	0.17	0.69	0.61	0.018
63	37	3571	36	2189	0.51	0.62	0.38	0.13	0.75	0.62	0.017
64	36	3629	37	2131	0.49	0.63	0.37	0.12	0.75	0.63	0.017
65	36	3688	37	2072	0.49	0.64	0.36	0.13	0.73	0.64	0.017
66	35	3745	38	2015	0.48	0.65	0.35	0.13	0.73	0.65	0.017
67	35	3803	38	1957	0.48	0.66	0.34	0.14	0.71	0.66	0.018
68	35	3860	38	1900	0.48	0.67	0.33	0.15	0.69	0.67	0.018
69	34	3918	39	1842	0.47	0.68	0.32	0.15	0.69	0.68	0.018
70	34	3976	39	1784	0.47	0.69	0.31	0.16	0.66	0.69	0.019
71	33	4033	40	1727	0.45	0.70	0.30	0.15	0.66	0.70	0.019
72	31	4089	42	1671	0.42	0.71	0.29	0.13	0.68	0.71	0.018
73	31	4146	42	1614	0.42	0.72	0.28	0.14	0.66	0.72	0.019
74	31	4204	42	1556	0.42	0.73	0.27	0.15	0.64	0.73	0.020
75	31	4262	42	1498	0.42	0.74	0.26	0.16	0.61	0.74	0.020
76	31	4321	42	1439	0.42	0.75	0.25	0.17	0.59	0.75	0.021
77	29	4378	44	1382	0.40	0.76	0.24	0.16	0.60	0.76	0.021
78	29	4437	44	1323	0.40	0.77	0.23	0.17	0.58	0.77	0.021
79	26	4493	47	1267	0.36	0.78	0.22	0.14	0.62	0.77	0.020
80	26	4552	47	1208	0.36	0.79	0.21	0.15	0.59	0.78	0.021
81	26	4611	47	1149	0.36	0.80	0.20	0.16	0.56	0.80	0.022
82	24	4668	49	1092	0.33	0.81	0.19	0.14	0.58	0.80	0.022
83	24	4727	49	1033	0.33	0.82	0.18	0.15	0.55	0.81	0.023
84	24	4786	49	974	0.33	0.83	0.17	0.16	0.51	0.82	0.024
85	22	4843	51	917	0.30	0.84	0.16	0.14	0.53	0.83	0.023
86	21	4901	52	859	0.29	0.85	0.15	0.14	0.52	0.84	0.024

87	21	4958	52	802	0.29	0.86	0.14	0.15	0.48	0.85	0.026
88	20	5016	53	744	0.27	0.87	0.13	0.14	0.47	0.86	0.026
89	20	5075	53	685	0.27	0.88	0.12	0.16	0.43	0.87	0.028
90	19	5133	54	627	0.26	0.89	0.11	0.15	0.42	0.88	0.029
Exports, h=6m											
57	46	3184	26	2517	0.64	0.56	0.44	0.20	0.69	0.56	0.018
58	45	3242	27	2459	0.63	0.57	0.43	0.19	0.69	0.57	0.018
59	44	3298	28	2403	0.61	0.58	0.42	0.19	0.69	0.58	0.018
60	43	3354	29	2347	0.60	0.59	0.41	0.19	0.69	0.59	0.018
61	42	3408	30	2293	0.58	0.60	0.40	0.18	0.69	0.60	0.018
62	41	3465	31	2236	0.57	0.61	0.39	0.18	0.69	0.61	0.018
63	41	3523	31	2178	0.57	0.62	0.38	0.19	0.67	0.62	0.018
64	40	3581	32	2120	0.56	0.63	0.37	0.18	0.67	0.63	0.019
65	40	3640	32	2061	0.56	0.64	0.36	0.19	0.65	0.64	0.019
66	39	3696	33	2005	0.54	0.65	0.35	0.19	0.65	0.65	0.019
67	38	3752	34	1949	0.53	0.66	0.34	0.19	0.65	0.66	0.019
68	37	3808	35	1893	0.51	0.67	0.33	0.18	0.65	0.67	0.019
69	35	3864	37	1837	0.49	0.68	0.32	0.16	0.66	0.68	0.019
70	32	3918	40	1783	0.44	0.69	0.31	0.13	0.70	0.68	0.018
71	32	3975	40	1726	0.44	0.70	0.30	0.14	0.68	0.69	0.018
72	32	4033	40	1668	0.44	0.71	0.29	0.15	0.66	0.70	0.019
73	32	4089	40	1612	0.44	0.72	0.28	0.16	0.64	0.71	0.019
74	31	4146	41	1555	0.43	0.73	0.27	0.16	0.63	0.72	0.020
75	30	4203	42	1498	0.42	0.74	0.26	0.15	0.63	0.73	0.020
76	28	4260	44	1441	0.39	0.75	0.25	0.14	0.65	0.74	0.019
77	27	4318	45	1383	0.38	0.76	0.24	0.13	0.65	0.75	0.019
78	27	4377	45	1324	0.38	0.77	0.23	0.14	0.62	0.76	0.020
79	27	4436	45	1265	0.38	0.78	0.22	0.15	0.59	0.77	0.021
80	26	4494	46	1207	0.36	0.79	0.21	0.15	0.59	0.78	0.021
81	24	4551	48	1150	0.33	0.80	0.20	0.13	0.61	0.79	0.020
82	22	4608	50	1093	0.31	0.81	0.19	0.11	0.63	0.80	0.020
83	21	4666	51	1035	0.29	0.82	0.18	0.11	0.62	0.81	0.020
84	21	4725	51	976	0.29	0.83	0.17	0.12	0.59	0.82	0.021
85	21	4784	51	917	0.29	0.84	0.16	0.13	0.55	0.83	0.022
86	20	4842	52	859	0.28	0.85	0.15	0.13	0.54	0.84	0.023
Exports, h=9m											
67	39	3733	33	1968	0.54	0.65	0.35	0.20	0.64	0.65	0.019
68	37	3789	35	1912	0.51	0.66	0.34	0.18	0.65	0.66	0.019
69	36	3846	36	1855	0.50	0.67	0.33	0.17	0.65	0.67	0.019
70	36	3904	36	1797	0.50	0.68	0.32	0.18	0.63	0.68	0.020
71	35	3960	37	1741	0.49	0.69	0.31	0.18	0.63	0.69	0.020
72	34	4018	38	1683	0.47	0.70	0.30	0.18	0.63	0.70	0.020
73	32	4073	40	1628	0.44	0.71	0.29	0.16	0.64	0.71	0.019
74	32	4132	40	1569	0.44	0.72	0.28	0.17	0.62	0.72	0.020
75	31	4189	41	1512	0.43	0.73	0.27	0.17	0.62	0.73	0.020
76	30	4248	42	1453	0.42	0.75	0.25	0.16	0.61	0.74	0.020
77	30	4307	42	1394	0.42	0.76	0.24	0.17	0.59	0.75	0.021
78	29	4366	43	1335	0.40	0.77	0.23	0.17	0.58	0.76	0.021

79	28	4425	44	1276	0.39	0.78	0.22	0.17	0.58	0.77	0.021
80	27	4483	45	1218	0.38	0.79	0.21	0.16	0.57	0.78	0.022
81	27	4543	45	1158	0.38	0.80	0.20	0.17	0.54	0.79	0.023
82	26	4601	46	1100	0.36	0.81	0.19	0.17	0.53	0.80	0.023
83	25	4659	47	1042	0.35	0.82	0.18	0.16	0.53	0.81	0.023
84	25	4719	47	982	0.35	0.83	0.17	0.17	0.50	0.82	0.025
85	23	4776	49	925	0.32	0.84	0.16	0.16	0.51	0.83	0.024
86	21	4834	51	867	0.29	0.85	0.15	0.14	0.52	0.84	0.024
87	21	4891	51	810	0.29	0.86	0.14	0.15	0.49	0.85	0.025
88	20	4950	52	751	0.28	0.87	0.13	0.15	0.47	0.86	0.026