Currency Crises During the Great Recession: Is This Time Different?*

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Abstract

During the 2007-2009 financial crisis the foreign exchange market was characterized by large volatility and wide currency swings. In this paper we evaluate whether during the period of the Great Recession there has been a structural break in the relationship between fundamentals and exchange rates within an early-warning framework. This is done by extending the original data set by Kaminsky and Reinhart (1999) and including not only the most recent period, but also 17 new countries. Our analysis considers two variations of the original early-warning system. First, we propose two new methods to obtain the probability distribution of the early-warning indicator (conditional on the occurrence of a crisis) – one fully parametric and one based on a novel distribution-free semi-parametric approach. Second, we compare the original early-warning indicator with a core indicator that includes only "pseudo-financial variables" (domestic credit/GDP, the real exchange rate, international reserves and the real interest-rate differential) and we evaluate their performance not only for currency crises during the Great Recession, but also for the Asian Crisis. All tests make us conclude that "this time is different", i.e. early-warning systems based on traditional macroeconomic variables have not only failed to forecast currency crises during the Great Recession, but have also significantly worsened with respect to the period of the Asian crisis.

Keywords: **Early Warning Systems**, **Exchange Rates**, **Semi-parametric Methods**.

JEL Classification Codes: F31, F47, F30.

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1 Introduction

One important aspect of the 2007-2009 financial crisis is the rapid increase in volatility in the foreign exchange market and the occurrence of large currency swings. Currencies of some emerging economies depreciated sharply against the dollar and the euro, while capital flows have been redirected to advanced economies in a typical "flight to safety" phenomenon. For instance, in September 2008 Ireland and Colombia experienced respectively 22 and 13 per cent depreciation of their currencies with respect to the dollar. In November 2008 the Korean won lost 13 per cent of its value with respect to the dollar. In January 2009 Venezuela had a big drop in its foreign reserves, close to 40 per cent in dollar terms.

These sudden changes indifferently hit countries with very strong fundamentals that had experienced high GDP growth in the previous years and were following cautious macroeconomic policies, as well as other countries with weaker fundamentals. Hence, all types of currency crises occurred, both self-fulfilling as well as traditional Krugman (1979) type.

The financial crisis has given a new momentum to the literature on the identification of currency crises and, in particular, to the development of "Early Warning Systems" (EWS). For instance, the International Monetary Fund and the Financial Stability Board started an "early warning exercise" in November 2008[1] and some recent studies have considered the relationship between the recent financial crisis, international exposure and currency swings (see, for instance, Obstfeld and Rogoff, 2009, Lane and Milesi-Ferretti, 2010, Shi and Gao, 2010, Anzuini and Gandolfo, 2003, etc.), while others showed evidence of the difficult predictability of the recent crisis (see Rose and Spiegel, 2009; Frankel and Saravelos, 2010, provide a recent survey).

In this paper we deal with two main issues related to the rapid and wide changes in exchange rates during the period of the Great Recession 2007-2009.

The first issue regards the correct identification of the signal that comes from an early warning system. More exactly, the original EWS hinges on the construction of a composite indicator, whose support is simply positive with no upper bound, and the key empirical task is to obtain the probability of a future crisis associated with the values of the indicator. In this paper we propose two alternative methods for mapping the (positive and unbounded) values of the early warning indicator into its conditional distribution. Besides a simple probit model within the original KLR framework, in this paper we consider a semi-parametric distribution-free approach, based on Khan (2011), which results particularly suitable for our econometric framework.

The second issue deals with the dynamics of exchange rates during the Great Recession. More exactly, we want to evaluate the stability in the relationship between the fundamentals used in the original early-warning indicators and the exchange rates before and during the

[1] See <http://www.imf.org/external/np/exr/facts/ewe.htm>.

Great Recession. This is done not only by considering structural-stability tests, but also introducing an alternative early-warning indicator based on a core of mainly financial variables that we name "pseudo-financial indicator" and includes: domestic credit/GDP, the real exchange rate, international reserves and the real interest-rate differential. Given the financial nature of the currency crises in the last two decades, this latter indicator should perform at least as well as the original wider indicator. Indeed, we evaluate in-sample and out-of-sample performances of the original and the pseudo-financial indicators. In particular, we compare their out-of-sample performances not only during the last period, but also for the Asian Crisis. In the end, no striking differences appear between the original and our pseudo-financial indicator, but *both* indicators underperform in prediction during the Great Recession with respect to the Asian crisis. Together with all the other in-sample evidence, we conclude that the dynamics of exchange rates and their relationships with a large class of common real and financial fundamentals has changed when judged with their out-of-sample forecasting abilities.

Both analysis are conducted by means of an updated dataset of the original work on EWS by Kaminsky, Lizondo and Reinhart (1996) and Kaminsky and Reinhart (1999) (henceforth KLR and KR respectively). More specifically, the original sample of 20 countries is updated till January 2010 and we included other 17 new countries.

The paper is structured as follows. In Section 2 we summarize the construction of early warning systems and review part of the literature (this section can be skipped by readers who are familiar with this approach). Section 3 presents the critical issues when extending the original dataset and explains our way of dealing with those issues. In Section 4 we present the in-sample performance of the original KLR system in our new data set after replicating the original work by KLR. The two original advances of this paper are presented on the next sections.

First, Section 5 presents intuitively the distribution-free semi-parametric method due to Khan (2011) to construct the probability distribution of our indicators and Section 6 reports the performance of the original KLR composite indicator when using alternative methods to obtain its conditional probability distribution, i.e. the Khan (2011) semi-parametric methods, our parametric version of the KLR original method and three methods already used in the literature.

Second, in Section 7 we introduce a new pseudo-financial composite indicator to improve upon the original KLR indicator in the choice of the relevant macroeconomic variables and we report its in-sample performance.

Finally, in Section 8 we focus on the out-of-sample performances of the original and the pseudo-financial indicator by using the different methodologies proposed. We evaluate their their ability to signal the currency crises during the Asian Crisis in 1997 and the period of the Great Recession, 2006-2009. Section 9 concludes.

2 Early Warning Systems: the Basics and the Related Literature

The challenge of this strand of literature on Early Warning Systems (EWS) is to find a sensible combination of variables that could anticipate the occurrence of a crisis. Similarly to the geological problem of anticipating earthquakes, the main difficulty is to identify variables that could reliably signal the future occurrence of the event.

However, with more difficulties than for geologists, economists face the problem of correctly identifying crises in the first place (exchange-rate crisis in our case). Just like geologists measure earth vibrations and define an "earthquake" as an event where the vibration index surpasses a certain threshold, similarly economists would define a currency crisis as a situation when some specific (usually catastrophic) events occur.

However, differently from geologists, economists have to construct the index that would signal the presence of a currency-crisis and this measure would be less objective than the measures of earth vibration that geologists use. The construction of this index is key to identify the events under study and should be inspired by the main exchange-rate models.

2.1 The Market Pressure Index

KLR borrowed the "market pressure index" initially proposed by Eichengreen, Rose and Wyplosz (1994). The so-called "short" version of this index for country i at time t is given by:

$$I_{i,t} = \frac{\Delta E_{i,t}}{E_{i,t-1}} - \frac{\sigma_{E,i}}{\sigma_{R,i}} \frac{\Delta R_{i,t}}{R_{i,t-1}} \tag{1}$$

where $E_{i,t}$ is the exchange rate of the currency of country i against the dollar at time t (quantity of domestic currency per 1 US dollar), $R_{i,t}$ represents a measure of international reserves (minus gold) for country i at time t, $\sigma_{E,i}$ and $\sigma_{R,i}$ are the standard deviations of the monthly percent change, respectively, in the exchange rate and in the reserves. The ratio of the standard deviations works as an adjusting weight for the different volatilities and for the different units of measure of the two components of the index.

2.2 Indicator Variables and the Composite Index

Once the index is constructed, the next step is to determine the threshold that would identify a "currency-crisis" event. KLR proposed to consider a value for the threshold that is 3 standard deviations above the average of the index over the whole sample, but country-specific.

When the episodes of exchange rate crises are identified, then it is possible to consider a large set of (macroeconomic) variables whose time-series behavior is thoroughly observed around the crisis episodes in order to uncover which of them is able to anticipate the catastrophic event.

Following KLR, many studies have considered the 24-month window that anticipate the exchange rate crisis and observed whenever the time series of each variable was showing anomalous variations that could signal the forthcoming event. More specifically, for each of the selected macroeconomic variables the authors considered the 30 percentiles of their distribution and observed when each of these percentiles was crossed. This was considered a *signal* when the crossing was occurring in the 24-month pre-crisis period or a *noise* if no crisis was happening within the next 24 months.

Table 1: Classification of signals and noise

	Crisis in the next 24 months	No crisis in the next 24 months
Signal	$A_{k,\pi}$	$B_{k,\pi}$ (Type II Error)
No signal	$C_{k,\pi}$ (Type I Error)	$D_{k,\pi}$

Table 1 reports how to distribute the number of times each variable crosses the threshold of the π-th percentile ($\pi = 1, \ldots, 30$). Hence, $A_{k,\pi}$ is the number of times the variable k crosses the π-th percentile and a crisis occurs in the next 24 months; $D_{k,\pi}$ is the number of times the variable k does not cross the π-th percentile and a crisis does not occur in the next 24 months. In both latter cases our variable (and the relative π-th percentile threshold) is correctly signaling the crisis or its absence.

The other two cases are instead incorrect signals, or noise. $C_{k,\pi}$ and $B_{k,\pi}$ are the number of times the variable k (and the relative threshold associated to the π-th percentile), respectively, does not signal the crisis when this actually occur and does signal the crisis when this does not occur in the next 24 months. In other words, they represent respectively type I and type II error. The key element of this stage is then the *noise-to-signal ratio* (NSR henceforth) constructed as follows:

$$NSR_{k,\pi} = \frac{B_{k,\pi}/(B_{k,\pi} + D_{k,\pi})}{A_{k,\pi}/(A_{k,\pi} + C_{k,\pi})}, \qquad \pi = 1, \ldots, 30 \tag{2}$$

KLR call such a scalar "*adjusted* NSR".[2]

The initial aim of the analysis is to identify for each variable k the π-th percentile-threshold that would minimize the NSR. This is done by pooling the data for all countries. Once determined the optimal π^* for each variable, the informational content of all the selected variables is combined to form a composite indicator that considers the good signals coming

[2]Berg and Pattillo (1999) note that the optimal threshold does not change if one just minimizes $B_{k,\pi}/A_{k,\pi}$, since $(A_{k,\pi} + C_{k,\pi})/(B_{k,\pi} + D_{k,\pi})$ is a function of the frequency of crises in the data and does not depend on the threshold.

from all the variables (when crossing their optimal thresholds).

In other words, when a variable crosses its own threshold, it issues a warning. But the fact that two or more variables are signalling a crisis in the same month brings a lot more information. Kaminsky et al. (1998) proposed the construction of a composite indicator by summing up all the signals issued by each indicator period by period and adjusted by their accuracy in terms of NSR. Let us notice that the composite indicator is now country-specific.

More formally, let us be $X_{k,i,t}$ one of the $k = 1, \ldots, K$ signalling macroeconomic variables for country i at time t and be $\bar{X}_{k,i}$ the relative threshold corresponding to the π_k^*-th percentile and the minimum NSR ω_k^*. Hence, each variable k issues a crisis signal when $X_{k,i,t} \geq \bar{X}_{k,i}$. This can be mapped into a dichotomic variable $S_{k,i,t}$ that takes value 1 if a signal is issued at time t by the variable k for country i.

The composite weighted indicator for country i at time t, $G_{i,t}$, is then obtained by summing up, period by period, all the signals coming from the all the K variables, but weighing them with their optimal NSR:

$$G_{i,t} = \sum_{i=1}^{K} \frac{S_{k,i,t}}{\omega_k^*}. \tag{3}$$

2.3 The Probability Distribution of the Composite Indicator

This indicator is a step function with indefinite positive support. The next important step is to obtain its probability distribution conditional on the event of a crisis within the next 24 months. This is done piecewise and is approximated by the following definition:

$$P(\textit{crisis between time t and (t+24)} \quad | \quad \overline{G}_l < G_t < \overline{G}_m) = \tag{4}$$

$$\frac{\#\textit{ months with} \quad \overline{G}_l < G_t < \overline{G}_m \quad \textit{and crisis between time t and (t+24)}}{\#\textit{ months with} \quad \overline{G}_l < G_t < \overline{G}_m}$$

where the ranges $\overline{G}_l$ and $\overline{G}_m$ are subjectively determined depending on the shape of the empirical distribution. Once the conditional probability for each arbitrary interval of G is known, it is also possible to obtain the time series of conditional probabilities by mapping each value of G_t into its conditional probability.

This can be named as the "complete" KR-KLR EWS. It has the great advantage that it can issue probability measures of crises in a fully nonparametric approach. However, its main disadvantage is that it relies on too much craftsmanship by the researcher in the determination of the probability distribution.

An near alternative EWS is proposed by Berg and Pattillo (1999). Differently from KLR, it relies on a fully parametric probit specification to generate the conditional probabilities of crises, but the model selection still hinges on the NSR analysis since the included variables

Table 2: Methods to obtain the conditional probability distribution of the composite indicator proposed in the literature

Method	*Characteristics*	*Reference*
KLR	Nonparametric	Kaminski et al. (1998)
BP linear	Parametric by using a probit	Berg and Pattillo (1999)
BP piecewise	Parametric by using a probit with nonlinear terms	Berg and Pattillo (1999)

are the "best" $K'(< K)$ variables in the NSR sense.

More specifically, in this paper we will consider two probit models referred to Berg and Pattillo (1999).

The first one we name it *BP linear* and consider the following probit specification:

$$P(C_{i,t}|\mathbf{X}_{i,t}) = \Phi\left\{\beta_0 + \sum_{k=1,\ldots K'} \beta_{1,k}\hat{F}(x_{k,i,t})\right\} \tag{5}$$

where $\hat{F}(x_{k,i,t})$ is the value of the empirical CDF of the variable k in the country i at any time t.

A second specification is named *BP piecewise* in this paper and, differently from the previous model (5) includes two additional (nonlinear) terms:

$$P(C_{i,t}|\mathbf{X}_{i,t}) = \Phi\left\{\beta_0 + \sum_{k=1,\ldots K'} \beta_{1,k}\hat{F}(x_{k,i,t}) + \sum_{k=1,\ldots K'} \beta_{2,k}S(x_{k,i,t}) + \right. \tag{6}$$

$$\left. + \sum_{k=1,\ldots K'} \beta_{3,k}S(x_{k,i,t}) \cdot [\hat{F}(x_{k,i,t}) - \pi_k)]\right\}$$

where $S(x_{k,i,t})$ is a dummy that takes the value 1 if the variable k emits a signal at time t in country i; in other words, it coincides with the indicator $S_{k,i,t}$ in equation (3). The last term is a variable that captures possible nonlinearities between the signal and the severity of the signalling itself. As mentioned above, the selection of the best K' macro variables is obtained by considering their own NSRs. Countries and time are all pooled together.

Table 2 summarizes the existing procedure. In this paper we will propose two additional methods (see Sections 5 and 6).

2.4 How to Judge EWS Performance

The evaluation of the forecasting ability of an EWS is done with two methods that are quite common in the literature: the *quadratic probability score* and an overall Goodness-of-Fit measure based on computed conditional probabilities.

The quadratic probability score (QPS), is defined as $QPS = \frac{1}{NT}\sum_{j=1}^{NT} 2 \cdot (P_j - C_j)^2$. It measures how distant the predicted probabilities P_j are (on average with a squared metrics) from the corresponding realizations (C_j takes value of 1 if there is a crisis at observation j and zero otherwise). This is an overall measure built with pooled data. A value of zero means perfect accuracy.

Evaluating the forecasting performance of an EWS means to judge its ability of signalling correctly the occurrence of a crisis versus tranquil periods. The first question is to determine when the indicator emits a signal. Given the predicted conditional probability of a crisis at any given point in time as determined in (4), we need to select an (arbitrary) probability cutoff τ such that there is a signal of a crisis when this is crossed. Then, in formal terms, a signal is emitted if $P(C|\Omega) > \tau$, where $P(C|\Omega)$ is the probability of having a crisis under the information set Ω and computed as in (4). The probabilities related to all possible events are reported in Table 3.

Table 3: Classification of Signals and Noise given a Probability Cutoff (τ)

	$C = 1$ (*Crisis*)	$C = 0$ (*No Crisis*)	
$S = 1$ *if* $P(C\|\Omega) \geq \tau$ (*Signal*)	$P(C = 1 \cap S = 1)$	$P(C = 0 \cap S = 1)$	$P(S = 1)$
$S = 0$ *if* $P(C\|\Omega) < \tau$ (*No Signal*)	$P(C = 1 \cap S = 0)$	$P(C = 0 \cap S = 0)$	$1 - P(S = 1)$
	$P(C = 1)$	$1 - P(C = 1)$	

Following Berg and Pattillo (1999), we refer to *Sensitivity* and *Specificity* (for a given τ), which are respectively the percentage of crises correctly called — i.e. $P(S = 1|C = 1)$ — and the percentage if tranquil periods correctly called — i.e. $P(S = 0|C = 0)$. Moreover, the overall percentage of observations correctly called, that is $P(C = 1 \cap S = 1) + P(C = 0 \cap S = 0)$, is also of interest.

All these estimated probabilities are important for policy makers, but their reliability and their actual use depend on the chosen probability cutoff. In fact, a high percentage of observations correctly called does not say anything about the validity of the model, because if for example the cutoff τ is too high the model gives almost no false alarms, the percentage is very high, but there is no point in using a model that predicts only tranquil periods.

A model that fits well the data should have all percentages high, and a percentage of false alarms relatively low. Following the literature, two conditions can be used to evaluate the validity of the model: *i)* $P(C = 1|S = 1) > P(C = 1)$, i.e. the probability of a crisis conditional to the information set must be greater than the unconditional probability of having a crisis in 24 months; *ii)* $P(S = 1|C = 1) + P(S = 0|C = 0) > 1$, i.e. the sum of Specificity and Sensitivity should be greater than the unity.

This latter approach is more general than the simple QPS and facilitates the comparison between parametric, semi-parametric and nonparametric methods.

3 A Country-Time Extension of the KR EWS: Critical Issues

In this section we consider a series of issues that have been raised when extending the original KLR sample both in the spatial dimension (i.e. by including 17 new countries) and in the time dimension (i.e. by considering the more recent period until January 2010). These additions increase the number of degrees of freedom, but increase also the variability and the diversity of situations by implying a revision in some parts of the original KLR EWS.

3.1 First Issue: Identifying Currency Crises

As mentioned above, the identification of currency crises is mandated to a "market pressure index" (MPI) and in particular to its outliers. They were originally identified by KLR as the time periods when the index crossed the sample average plus three times the sample standard deviation.

The original dating of all the crises was obtained by KLR not only applying their mechanical algorithm, but also including subjectively some crisis episodes that the algorithm was missing. Indeed, some episodes labeled as crises by KLR-KR are simply not signalled by the MPI. More specifically, Goldstein, Kaminsky and Reinhart (2003) claim that the MPI "suggests" the presence of crises, but that their occurrence should actually be identified by also using institutional data and other sources.

This drawback characterizes also the post-1996 period and our geographically-extended sample. In particular, some evident episodes of currency crises (e.g. the December 2001 Argentine devaluation) were not signalled by the MPI. We deem that the subjective correction proposed in the early literature, although necessary to identify all possible known crises, reveals a failure of the MPI or of its threshold.

Hence, we explored changes in crisis detection, in particular by varying the determination of the MPI threshold along two lines in order to take into consideration the longer time span. First, we considered two time-varying ways of computing mean and standard deviation of the index and, therefore, the signaling threshold:[3] (i) a *rolling* threshold, by keeping the initial date (1970:1) fixed and moving the final date period by period; (ii) a *moving* threshold by considering a moving window of 60 months to compute the standard deviation. Moreover, we also considered two separate samples, 1970:1-1981:12 and 1982:1-1996:12.

[3] We have also changed the level of the threshold by considering two and two and a half standard deviations above the mean, as also experimented in other contributions (see Berg et al., 2004). Of course, this variation induced an increase in the number of crisis episodes. However, it did not improve the average performance of the EWS. Results are available from the authors upon request.

3.2 Second Issue: How to Compare the Results for the Extended Sample?

We extend the analysis of the original KLR work by considering a new dataset along two lines, the time dimension (from 1970-1996 to 1970-2010) and the country dimension (including 17 new countries).[4] Would the crisis identification mechanism be robust to this extension? Would the same algorithm be able to signal the main crises that occurred (according to common wisdom) after 1996? Which problems of instability may occur by extending the sample in the first decade of the 21st century and widening the country sample?

We address these questions by considering four subsamples from our full sample (named FS, including 37 countries from 1970:1 to 2010:1):

- the original KR sample (named KR, with 20 countries from 1970:1 to 1995:12), which is mainly used to check for robustness with respect to the original analysis;
- the original KR country sample extended till 2010 (named KR+T, with the original 20 countries from 1970:1 to 2010:12) as a simple time extension of the original country set;
- the original KR country sample extended till 2005 (named KR-FOR, with the original 20 countries from 1970:1 to 2005:12) to check the ability to forecast the recent crisis within the KR sample;
- the full sample till 2005 (named F-FOR, with 37 countries from 1970:1 to 2005:12) to check the ability to forecast the recent crisis within the larger sample.[5]

As mentioned in the previous sections, the metrics of our comparison will be centered on the NSR of each variable included in the EWS and on the changes in the percentile threshold of each variable, indicating a change in its alert value.

In the new full sample FS the number of crisis episodes increases. Table 14 summarizes the crisis episodes identified with our methods and compare them with the original KR dating.

3.3 Third Issue: Obtaining the Probability Distribution of the Composite Indicator

In general, we found that the KR-KLR framework relies too much on "human intervention" by the researcher. On the contrary, we believe that an EWS should be as much automatic as possible in order to assure replication and extension. In particular, the mapping from the

[4]See Appendix A.

[5]The extension of the original KR time sample 1970-1995 to the new 17 countries would not be possible since most of them are Eastern European countries that either would not exist before the 1990s or were not market economies.

composite indicator to its conditional probability reported in (4) requires a lot of tailoring work in choosing the best intervals so as to assure that the probabilities be increasing in G and be close to the value of 1 when G is at its maximum. In our replication computed probabilities are not always monotonically increasing and the probability associated to the maximum level of G remains low, as it is common to other studies.

As an alternative, Berg and Pattillo (1999) propose a probit model with two different specifications (see Section 2.3 and Table 2).

In this paper, one of the contributions is to improve upon the existing methods to derive the conditional probability of the composite indicator and we propose two alternatives.

The first one takes a fully parametric approach to obtain the distribution of the indicator by fitting a pooled probit specification to the crisis indicator G_j ($j = 1, \ldots NT$):

$$P(C_j|G_j) = \Phi(\beta_0 + \beta_1 G_j)$$

Since this is a mixture of the original KLR method, but adding a probit model to derive the conditional probability of the composite indicator, we name this method as *KLR Probit*.

The second method that we propose is based on the semi-parametric approach and is based on the recent advancement proposed by Khan (2011) for discrete choice models. This will be presented in Section 5, whereas in the next Section 4 we present the results of our (time and geographic) extensions with the original KLR before considering the other methods.

4 The In-Sample Performance of the Original EWS after 1995

In this section we perform a first evaluation of the original EWS proposed by KLR when extending the sample to the most recent period and to a larger set of countries. Within this EWS we already get some important indications on its performance in the most recent period. This is already an important result before considering alternative methods and alternative indicators.

4.1 Robustness: Our Replication of the Original KR EWS

As a first step of our analysis, we replicate the original work by using the same set of 16 macroeconomic variables proposed in the literature. This is only the starting point of our analysis before proposing different extensions and considering that the replication of the KR EWS is not banal. In particular, some specific choices and assumptions have to be clearly stated:

- *How to treat missing data.* Correcting for missing data is a delicate issue. We decided to restrict the set of signals only to the "feasible" signals, i.e. to the ones for which data exists. More exactly, for each indicator we excluded all the observations for which data did not exist. In terms of entries in Table 1, we excluded entries both in the A field (i.e. a signal when the crisis occurs) and in the C field (i.e. absence of signal when the crisis occurs). In other words, we deemed that an indicator could not be blamed for not signaling a crisis if it does not exist. It is not clear what other authors do.

- *The minimum threshold.* Another issue is that, since the NSR tends to be increasing in π, the percentile where to start is a crucial choice. The optimal critical region of rejection of a tranquil period is generally at the first percentile, or very close to it. But this leads to thresholds that are too restrictive to be useful for early warning purposes since they occur too rarely. Also, the empirical quantile tends to have a higher variance at the tails of the distribution.[6] KLR, Berg and Pattillo (1999) and Edison (2000) start from the 10th percentile, whereas Goldstein, Kaminsky and Reinhart (2000) start from the first one (while KR do not specify). We decided to start from the 5th percentile (which yields better results in terms of low average NSR).

We applied our algorithm with the updated dataset and the new list of currency crises is available in Table 14 in the Appendix. In particular, we report all the crises originally recorded in KR together with the ones we identify with the fixed threshold and with the different time-varying methods cited in Section 3.1. As mentioned above, we choose the fixed threshold method with three standard deviations above the mean for all further analysis.

Results of our reruns are provided in Table 4, along with the original results by KR and previous attempts by other researchers to replicate the same work. In particular, in the Table we consider two different reruns depending on whether we considered the crisis episodes identified by our algorithm (Rerun I) or whether considering the original KR dating (Rerun II).

On average the NSR of the rerun with the KR dates (Rerun II) almost coincides with the original work (0.71 vs. 0.70), but even when considering the crises identified by our algorithm (66 instead of 76 in KR) the performance is not very different (0.77 vs. 0.70). These NSR's are certainly lower and closer to the original KR's than the ones obtained by other attempts in the literature by Berg and Pattillo (1999) and Edison (2000).

We deem that our ability to replicate sufficiently well the original KR contribution of the macroeconomic indicators (notwithstanding the data revisions and the complexity of the construction of the dataset) is a good starting point for the rest of the analysis.

[6] The asymptotic variance of the sample quantile function $\hat{Q}(\pi)$ is: $AsVar(\hat{Q}(\pi)) = \frac{\pi(1-\pi)}{f(Q(\pi))^2}$. Hence, it has a U form and attains a minimum at the median. This means that the asymptotic variance is very large in the tails and it is appropriate to eliminate the first, noisier percentiles.

Table 4: Comparison with the Literature of the Noise-to-Signal Ratios of the Indicators in the EWS (original sample: 20 countries, 1970:1-1995:12; number of identified crises in parenthesis).

	Rerun I (our crisis dates) (66)		Rerun II (KR crisis dates) (76)		KR (76)		Berg and Pattillo (1999) (14 diff.)		Edison (2000) (70)	
Indicators	NSR	π^*	NSR	π^*	NSR	π^*	NSR	π^*	NSR	π^*
M2 Multiplier	0.69	5	0.70	5	0.67	14	0.8	16	0.89	15
Domestic Credit/GDP	0.72	24	0.69	21	0.64	10	0.71	15	0.63	10
Real Interest Rate	1.29	29	0.88	11	0.75	12	0.74	18	0.69	15
Lending/Deposit rate	1.10	29	1.19	29	1.52	20	1.44	11	2.3	20
Excess M1	0.71	5	0.54	5	0.56	6	0.69	10	0.6	10
M2/Reserves	0.57	5	0.50	14	0.52	13	0.46	13	0.54	10
Bank Deposits	0.77	21	0.78	17	0.67	10	1.53	10	1.05	10
Exports	0.44	6	0.36	6	0.40	10	0.49	10	0.52	10
Terms of Trade	1.00	17	0.84	8	0.70	16	1.42	20	ND	ND
Real Exchange Rate	0.26	6	0.20	6	0.14	10	0.24	10	0.22	10
Imports	1.11	6	0.83	5	1.10	10	1.19	10	1.2	10
Reserves	0.38	6	0.54	9	0.55	15	0.53	11	0.57	10
Real Interest Rate Diff.	0.84	5	0.70	5	0.90	11	1.97	18	1.2	10
Industrial Production	0.87	6	0.63	6	0.46	11	1.23	15	0.57	12
Stock Market	0.50	8	0.47	7	0.38	11	1.81	13	0.57	20
Gov. Deficit/GDP	1.18	25	1.47	5	1.17	14	NA	NA	NA	NA
Average	0.77		0.71		0.70		1.02		0.83	

Source: authors' computations; for the dataset see Appendix A.

4.2 Country- and Time-Extension: Indications from the Performance of the Original EWS

The next exercise is to compare the performance of the original EWS in the new samples. However, since the performance of the EWS is based on the composite indicator, first we want to evaluate the changes in the NSRs and threshold percentiles across all the subsamples. The results are reported in Table 5.

An eyeballing comparison of the NSRs seems to show that they are quite stable across time and countries. The KR EWS is then robust if we expand the sample along both dimensions. Of course, some indicators tend to improve their early-warning ability, while others tend to worsen it. Robustness when including new countries can be checked by comparing the KR-FOR and F-FOR samples. Differences are barely noticeable on average and for the single variables. The same can be said for the time extension, that is by looking at KR and KR-FOR, while a comparison between KR and F-FOR (country-time robustness) yields the same results. The only noticeable changes arise when we expand the sample to include observations from 2005:12 to 2010:1, i.e. comparing the subsamples KR-FOR and F-FOR with the relative full samples, i.e. KR+T and FS. In particular, two relevant real variables (exports and output) experience an increase both in the NSR and in the optimal percentile. This lets us think that something has changed in the predictive power of these variables in the latter five years. We

Table 5: Comparison among the Noise-to-Signal Ratios and threshold percentiles of the Indicators under the original KR sample (our rerun with our crisis dating) and the extended samples.

	KR		KR+T		KR-FOR		F-FOR		FS	
	NSR	π^*	NSR	π^*	NSR	π^*	NSR	π^*	NSR	π^*
M2 Multiplier	0.69	5	0.79	5	0.84	6	0.85	6	0.85	5
Domestic Credit/GDP	0.72	24	0.61	20	0.63	21	0.64	23	0.69	22
Real Interest Rate	1.29	29	0.62	29	0.73	29	0.66	29	0.66	29
Lending/Deposit Rate	1.1	29	1.97	28	1.72	29	1.83	29	1.92	29
Excess M1	0.44	5	0.93	16	0.6	5	0.54	5	0.69	5
M2/Reserves	0.57	5	0.58	5	0.49	5	0.53	5	0.69	5
Bank Deposits	0.77	21	0.96	27	0.93	28	0.83	28	0.73	16
Exports	0.44	6	0.65	7	0.54	5	0.67	7	0.77	19
Terms of Trade	1.00	17	0.95	17	1.03	17	0.97	7	0.97	7
Real Exchange Rate	0.26	6	0.2	5	0.19	5	0.24	5	0.21	5
Imports	1.11	6	0.94	5	1.00	6	1.00	6	1.07	5
International Reserves	0.38	6	0.46	9	0.44	8	0.47	7	0.5	9
Real Interest Rate Diff.	0.84	5	0.61	5	0.71	5	0.64	22	0.66	5
Output	0.87	6	1.06	28	0.86	10	0.82	10	1.03	25
Stock	0.5	8	0.74	28	0.7	14	0.68	28	0.69	28
Deficit/GDP	1.18	25	0.74	12	0.91	14	0.86	14	0.76	11
Average	0.76		0.8		0.77		0.76		0.81	

Source: authors' computations; for the dataset see Appendix A.

will address this issue in detail in Section 8.

The in-sample performance of the original EWS is reported in Table 6 for two different values of the signaling threshold (τ equal to 0.25 and 0.50) across all the samples, starting with the original KR sample to the full sample.

When considering the most conservative threshold at 0.50, the EWS performs well in all the subsamples, showing an increase in the percentage of correctly called signals and in the general trustworthiness of the indicator (i.e. a high value in $P[C|S]$). However, signals activated at the 50 per cent probability threshold perform well because they correctly call tranquil periods (see the high value in "Specificity"), but are useless in predicting the occurrence of the crises (i.e. the value of "Sensitivity" is close to zero).

A more interesting result is obtained when looking at the threshold $\tau = 0.25$.[7] In this case the value of Sensitivity increases and Specificity is still high. Their sum is always higher than 1 for all the samples. In terms of correctly called crises, the extension of the sample along the time (see both KR+T and KR-FOR) and the country dimension (see F-FOR and FS) seems to improve the performance. But this is mainly due to the improved ability to predict tranquil periods rather than crises — especially when comparing FS with all the other subsamples.

At the threshold $\tau = 0.25$ other interesting indications come from Sensitivity and Specificity. When looking only at the original KR 20 countries, Sensitivity (i.e. the ability of anticipating crises) is equal to 34 per cent in the original subperiod 1970-1995. Sensitivity drops in the larger sample 1970-2005 for both the original 20 countries (i.e. KR-FOR subsample) and the full sample of the 37 countries (i.e. F-FOR subsample), being respectively 23.01 per cent to 20.63 per cent.

However, a much more remarkable fall is observed when including the more recent years after 2005 in the full sample (FS). Sensitivity collapses to 4.31 per cent. A similar drop is not observed when considering only the original KR 20 countries in the full sample since Sensitivity remains equal to 23.01, i.e. very similar to the value for the KR-FOR sample (23). Hence, a structural break in the performance of the indicator is due to the particular bad performance for the new countries, but only in the recent years after 2005.

Hence, the lower predictive power of the original KR EWS seems to be attributed to the bad performance for the new 17 countries in the sample, although their bad contribution is confined only in the very last period 2006-2010, i.e. the period closely coinciding with the Great Recession.

Hence, we cannot exclude a generalized failure in the performance of the KR EWS due to the peculiarity of the post-2005 period. Using alternative methods for the construction of the conditional probability distribution of the composite indicator (Sections 5 and 6) or introducing a new, more-focused indicator (Section 7), may give more insights as presented in

[7]The choice of this threshold is due also to facilitate comparison with literature

Table 6: In-sample Goodness-of-Fit for the Different Samples and for Different Signaling Thresholds: Conditional Probabilities Based on the Intervals of the Composite indicator (KLR method)

	KR	KR+T	KR-FOR	F-FOR	FS
$\tau = 0.5$					
Correctly called	80.48	84.75	83.56	88.69	88.53
Sensitivity	0.16	1.36	1.19	0.00	0.29
Specificity	99.00	99.83	99.00	100.00	99.00
$1 - P(C\|S)$	33.33	41.18	34.62	None called	40.00
$\tau = 0.25$					
Correctly called	75.00	80.44	82.00	85.57	87.84
Sensitivity	34.00	23.01	23.00	20.63	4.31
Specificity	85.00	90.82	93.00	93.85	99.00
$1 - P(C\|S)$	63.90	68.81	59.88	70.04	70.37

Source: authors' computations; for the dataset see Appendix A.

the following sections.

5 Advancement 1: A Semi-parametric Approach for the Probability Distribution of the Composite Indicator

As pointed out in Section 3.3, one of the critical steps when building the EWI is the construction of the probability distribution of the composite indicator. In the literature two approaches have been followed so far: a nonparametric method, as in KLR and following studies, and a fully parametric approach, as in Berg and Patillo (1999) and others.

The recent new advances in the field of semi-parametric methods of estimation offer a new possibility that we consider here as a first advancement with respect to the original approach. A failure in the scarce performance of different EWS may be due to the use of improper methods as required by the nature of the data and of the phenomena in the construction of the probability distribution of the composite indicator.

In the following section we give a short presentation of semiparametric methods and, although still at an intuitive level, we illustrate more thoroughly the sieves approach and the Khan (2011) method.

5.1 Semi-parametric Methods and the Sieve Approach

In the classical parametric approach,[8] it is typically assumed that the dependent variable is functionally dependent on the conditioning variables ("regressors") and the unobservable "errors" according to a fixed structural relation of the form:

$$y = g(x, \beta_0, \epsilon; \gamma_0)$$

where the function $g(\cdot)$ is known, β_0 is the vector of the unobserved finite-dimensional "parameters of interest", ϵ is the idiosyncratic stochastic component and γ_0 is the vector of "nuisance parameters". The form of the $g(\cdot)$ function is usually chosen in order to have a simple and interpretable data generating process.

Since the previous equation does not hold exactly for any value of the parameters, we interpret ϵ as the stochastic part and, in parametric methods, we "force" it to belong to a finite-dimensional family of distributions where the vector γ_0 is finite (e.g. in the normal distribution γ_0 includes mean and variance of the distribution).

Once the conditional distribution given $g(\cdot)$ is known, the conditional distribution of y given x can be derived. Then, if both the specification of $g(\cdot)$ and the error distribution are correct, all the parameters (β_0 and the nuisance parameters of the conditional distribution of the error, γ_0) can be estimated consistently. Instead, in case of nonlinear $g(\cdot)$, misspecification of the error distribution causes inconsistency of the MLE estimates and inconsistency of the conditional distribution of y given x.

Differently from the parametric model, a nonparametric approach assumes that the error term is fully separated from the functional form $g(\cdot)$, which becomes:

$$g(x) = H[F(y|x)]$$

where $F(y|x)$ is the conditional distribution of y given x and $H[\cdot]$ is a functional location measure. For example, if $g(x)$ is the mean regression function, i.e. the conditional expectation of y given x, $E[y|x]$, then $g(x) = H[F(y|x)] = \int y dF(y|x)$.

Hence, the model for y can be written as follows:

$$y = g(x) + \epsilon = E[y|x] + \epsilon$$

and ϵ has to satisfy the orthogonality condition: $E[\epsilon|x] = 0$.

In this case the interpretation of the error term is different: its stochastic properties derive from the assumptions on the function $g(\cdot)$ rather than assuming for ϵ an a priori distribution,

[8] Our description of semiparametric methods and sieve estimators follows loosely Powell (1994) and Chen (2007).

as in the parametric case.

A suitable estimator of $g(\cdot)$ (for a sample of n observations) is:

$$\hat{g}_n = H[\hat{F}_n(y|x)]$$

where the functional $H[\cdot]$ is known (it was the operator "expected value" above). In the nonparametric approach the main problem is an efficient estimation of the conditional distribution function of y given x, i.e. $\hat{F}_n(y|x)$.

The main advantage of nonparametric models is that they impose few restrictions on the form of the joint distribution of the data and so the misspecification of the functional form is less likely. On the other hand, the precision of the estimators based only on nonparametric restrictions is often poor. For example, when you estimates $g(\cdot)$ by smoothing the empirical cumulative distribution function (CDF) of the data, the rate of convergence is slower than in the parametric case because of the bias caused by the smoothing.

The semi-parametric approach is halfway between the two latter models since it considers jointly the regressors and the error term within the function $g(\cdot)$, as in the parametric case, but treats separately the behavior of the errors.

In a semi-parametric model we consider two components: the "parameters of interest" that link x to y, which are finite-dimensional, and nuisance functions related to the distribution of the error term, which are treated nonparametrically. More formally:

$$y = g\left(x, \beta_0, \epsilon; \gamma(\cdot)\right)$$

where β_0 is the unknown vector of parameters of interest that belongs to a finite-dimensional Euclidian subspace; $\gamma(\cdot)$ represents the nuisance functions that, differently from the parametric case, are unknown — or, said differently, involve the knowledge of nuisance parameters that lie in infinite-dimensional spaces.

In other words, in the semi-parametric approach the y–x relationship can be considered "parametric", whereas the error term characteristics are fully nonparametric.

It has been shown that it is possible to obtain consistent estimates of the nuisance parameters, although belonging to infinite-dimensional spaces, by means of the optimization of a criterion function that uses finite samples. This approach is named "sieve" since the approximation of the infinite-dimensional space is operated with less complex – and often finite-dimensional – parameter spaces that are called "sieves" (see Chen, 2007).

5.2 Semi-parametric Methods for Binary-Choice Models and the Khan (2011) Approach

Manski (1975, 1985) used a semi-parametric method to estimate binary choice models, which is the class of econometric models we are using in this paper. He solved the main problems related to these models, i.e. the inconsistency of the estimators under both heteroskedastic conditional error terms and misspecification of the error distribution. The identification of the parameters of interest β_0 is obtained by imposing that the conditional median be zero (conditional-median-restriction estimator).

However, the Manski (1975, 1985) approach has three main problems. First, it does not estimate choice probabilities. Second, it is very difficult to implement since the criterion function is not smooth. Third, it does not have good statistical properties (i.e. slow rate of convergence of the estimators and non-Gaussian limiting distribution).[9]

Khan (2011) proposes the application of the sieve approach to the binary choice models by using a "distribution-free" binary response estimator with a manageable implementation.[10]

Khan (2011) has shown that the binary response model $y_i = I\{x_i'\beta - \epsilon_i\}$ (where $I(\cdot)$ is an indicator function) with a null conditional-median restriction for identification is "observationally" equivalent[11] to a multiplicative heteroskedastic probit (or logit) model up to an unknown infinite-parameter scale function.

By using the sieve approach described above, the empirical implementation of Khan (2011)'s result is possible by the definition of a simple empirical criterion function. In particular, over the sample of n observations the estimator $\widetilde{\alpha}_n$ of all the parameters can be obtained by means of nonlinear least squares (NLLS) according to the following:

$$\widetilde{\alpha}_n = \min_{\alpha} \frac{1}{n} \sum_{i=1}^{n} \left\{ y_i - \Phi\left[x_i'\beta \cdot \gamma_n(x_i)\right] \right\},$$

where $\gamma_n(x)$ is the sieve base and, according to Khan (2011), this can be computed as an exponential function where the argument is any polynomial of the dependent variables; Φ is the normal CDF. The estimated vector $\widetilde{\alpha}_n$ contains both the estimates of β_0 and the nuisance parameters of the exponential $\gamma_n(x)$ that approximates the unknown "nuisance functions" $\gamma(\cdot)$. Choice probabilities can then be easily computed and are shown to be consistent.

More specifically, in this paper we estimate model (5), i.e. similar to *BP linear* but with a semi-parametric approach to estimation.

[9]Horowitz (1992) proposed a new approach by improving the implementation of the estimation procedure with a Gaussian limiting distribution.

[10]See Blevins and Khan (2010) for the actual implementation in Stata.

[11]That is, $P(y_i = 1|x_i = x)$ is the same in both models.

Table 7: Methods to obtain the conditional probability distribution of the composite indicator proposed in the literature

Method	*Characteristics*	*Reference*
KLR	Nonparametric	Kaminski et al. (1998)
BP linear	Parametric by using a probit	Berg and Pattillo (1999)
BP piecewise	Parametric by using a probit with nonlinear terms	Berg and Pattillo (1999)
KLR Probit	As KLR but parametric, normal CDF	this paper
Sieve NLLS	Semi-parametric version of BP linear	Khan (2011) (methodology)

6 What Insights from Using Different Methods to Obtain the Probability Distribution of the Composite Indicator?

Let us recall that the KLR method is fully nonparametric and suffers from different drawbacks for the construction of the conditional distribution of the composite indicator that have been recalled in Section 3.3 (i.e. difficulty in obtaining a monotonically increasing probability distribution; finding the maximum value of the unbounded indicator for which the probability distribution is close to one).

As still reported in Section 3.3, Berg and Pattillo (1999) take a different parametric approach by fitting a probit model where the conditional probability of a crisis is regressed on the main macroeconomic variables. We recalled two variants of the Berg and Pattillo (1999) approach by either including or excluding nonlinear terms (we named them, respectively, *BP piecewise* and *BP linear*).

Besides these methods, we propose a "more parametric" approach in the KLR EWS by fitting a normal probability distribution for the composite indicator by means of the following empirical model (we name it *KLR Probit*):

$$P(C_j|G_j) = \Phi(\beta_0 + \beta_1 G_j)$$

for $j = 1, \ldots, NT$.

Finally, we use the semi-parametric method described in Section 5 and, more specifically, the Khan (2011) approach to the estimation of binary-choice models within the class of sieve estimators (named it *Sieve NLLS*, since it involves nonlinear least squares within the sieve approach).

Table 8 reports the different measures of "goodness of fit" for all the samples. This is complementary to Table 6, where the goodness of fit is reported only for the original KLR method of reconstruction of the probability distribution of the composite indicator.

In terms of Sensitivity, these results confirm the drop in the performance of the EWS for

Table 8: In-sample Goodness-of-Fit for the Different Samples and for the Different Methodologies: Conditional Probabilities (Signaling Threshold: $\tau = 0.25$)

Sample	KR	KR+T	KR-FOR	F-FOR	FS
BP linear					
Correctly called	70.39	78.46	74.66	79.15	81.64
Sensitivity	53.86	28.07	40.65	35.50	21.13
Specificity	74.81	88.04	81.79	86.71	92.24
$1 - P(C\|S)$	63.64	69.13	68.10	68.38	67.70
QPS	30.14	25.51	26.38	23.18	24.36
BP piecewise					
Correctly called	72.31	80.65	77.14	80.58	82.46
Sensitivity	53.34	29.32	40.91	35.10	21.40
Specificity	77.38	90.41	84.74	88.45	93.15
$1 - P(C\|S)$	61.35	63.23	64.00	65.52	64.62
QPS	29.76	25.00	25.92	22.82	23.99
KLR probit					
Correctly called	76.27	82.43	81.04	87.11	87.04
Sensitivity	29.61	16.63	23.95	11.67	7.34
Specificity	87.59	94.33	92.35	96.73	97.38
$1 - P(C\|S)$	63.31	65.35	61.74	68.74	73.36
QPS	30.00	25.00	27.00	19.00	20.00
Sieve NLLS					
Correctly called	68.79	80.08	76.50	80.05	81.93
Sensitivity	61.90	30.98	40.99	35.67	26.67
Specificity	70.63	89.42	83.95	87.63	91.60
$1 - P(C\|S)$	63.97	64.27	65.11	66.51	64.25
QPS	29.83	23.84	25.90	22.90	23.84

Source: authors' computations; for the dataset see Appendix A.

the full sample with respect to all the other samples. Differently from Table 6 we note a systematic fall in sensitivity between 2006 and 2010, not only for the samples that include all 37 countries (i.e. F-FOR and FS), but also for the sample that include only the original KLR 20 countries (i.e. KR-FOR and KR+T).

Hence, the peculiarity of the last years around the Great Recession, independently on the geographical sample (i.e. either including or excluding the new 17 countries), seems to be confirmed by these latter results. The next experiment would be to consider an alternative composite indicators and see whether there can be an improvement in the predictability of currency crises with a different set of variables.

7 Advancement 2: An Alternative Pseudo-Financial EWI

In the Section 6 we have shown that, when using alternative methods for the construction of the probability distribution of the composite indicator, the EWS dramatically underperforms in the last period 2006-2010.

In this section we want to analyze whether the weakness of the EWS depends on the fact that too many irrelevant variables are contributing to the formation of the composite indicator, hence introducing too much noise.

Following the same steps as in the construction of a composite indicator, we then formed an alternative early warning indicator (EWI) that would focus on the best-performing (in terms of average NSR) pseudo-financial variables. More exactly, we considered: domestic credit/GDP, the real exchange rate, international reserves and the real interest-rate differential.

This new EWI combines both pure financial variables (like Domestic Credit/GDP and International Reserves) and real variables that we name "pseudo-financial" (i.e. the real exchange rate and the real interest-rate differential) since they are highly affected by their nominal component in the short run. The increasing importance of financial flows in the last two decades and the financial nature of the Great Recession are the additional, sensible reasons why to confine our indicator to these determinants.

Moreover, knowing in advance the NSR of all the variables that compose our pseudo-financial indicator, we are aware to select what could be the best of all possible alternative financial indicators *ex post*.

In other words, we are playing an unfair game knowing that the pseudo-financial indicator is including only the best macroeconomic variables. However, this is done on purpose to improve our EWS along the dimension of the best information set. We recall that our main purpose is to evaluate the stability of the relationship between the fundamentals and the exchange rates. Our new indicator should be the best on average, but our question is whether this is true all over the sample including the period of the Great Recession.

Table 9 reports the various indexes of performance for all our samples and for all methods to obtain the probability distribution of the new composite index.

As expected, the general performance of the new composite index improves according to the QPS and the probability of having a crisis when it is signalled (i.e. $P[C|S]$). More interesting is the comparison between the performances in terms of Sensitivity in the subsamples, especially KR-FOR vs. KR+T and F-FOR vs. FS, recalling that there was a sensitive decrease when including the last four years with the original composite indicators.

This latter result seems to be generally confirmed. This is consistently observed between KR-FOR and KR+T (except for *KLR Probit* for which there is a very slight improvement). Hence, with the original KR 20 countries, the last four years show a break even in the performance of the pseudo-financial indicator.

The same can be said also for the larger new sample of 37 countries when considering three out of five methods. Only when considering the original KLR method and its slight parametric variation (*KLR Probit*) there is an improvement in the Sensitivity of the new pseudo-financial indicator in the full sample.

Finally, we ought to notice that, just like in the case of original EWS (in Table 8), the distribution-free semi-parametric method (Sieve NLLS) performs best with respect to Sensitivity.

8 Is There a Structural Break during the Great Recession?

The empirical results shown thus far indicate that there is a discontinuity in the last four years of our sample. The performance of the composite indicator as an early-warning indicator seems to get worse when including the years 2006-2009 and this is confirmed when considering not only different methodologies in the (very sensitive) construction of the probability distribution of the composite indicators (Section 6), but also when choosing an *ad-hoc* well-performing pseudo-financial indicator (Section 7).

In this section we test formally the presence of a structural break in two different ways. First, we check whether there is instability in a probit model á la Berg-Pattillo (1999) by adding dummy variables for the different sample extensions. We focus on results for the time extension 2006-2009.

Next, we evaluate the out-of-sample performance of the original KLR EWS for the last period 2006-2009 and we compare it along two lines: first, with its out-of-sample performance for the Asian Crisis; secondly, with the out-of-sample performance of the pseudo-financial indicator (for both the Asian Crisis and the Great Recession period). This latter analysis

Table 9: In-sample Goodness-of-Fit of the Pseudo-Financial EWI for the Different Samples and for the Different Methodologies: Conditional Probabilities (Signaling Threshold: $\tau = 0.25$)

Sample	KR	KR+T	KR-FOR	F-FOR	FS
KLR method					
Correctly called	78.78	83.24	80.12	87.86	86.87
Sensitivity	23.54	19.01	27.38	13.38	16.64
Specificity	92.19	94.86	90.56	97.35	95.98
$1 - P(C\|S)$	57.73	59.94	63.53	60.78	65.06
QPS	0.29	0.24	0.25	0.19	0.19
BP linear					
Correctly called	71.78	79.93	76.88	79.90	81.50
Sensitivity	57.34	25.88	35.14	31.69	21.12
Specificity	75.59	89.18	85.19	87.90	91.49
$1 - P(C\|S)$	61.73	70.97	67.91	69.70	70.90
QPS	0.29	0.23	0.26	0.22	0.23
BP piecewise					
Correctly called	81.45	82.33	78.79	81.45	83.00
Sensitivity	36.63	31.17	38.53	36.63	24.64
Specificity	88.89	91.08	86.81	88.89	92.65
$1 - P(C\|S)$	64.63	62.60	63.21	64.63	64.32
QPS	0.21	0.22	0.24	0.21	0.22
KLR probit					
Correctly called	78.78	83.24	82.47	81.19	86.58
Sensitivity	23.54	19.01	18.77	0.00	16.89
Specificity	92.19	94.86	95.08	100.00	95.62
$1 - P(C\|S)$	57.73	59.94	56.98	-	66.67
QPS	0.29	0.24	0.26	0.31	0.19
Sieve NLLS					
Correctly called	70.71	83.34	76.20	78.21	81.42
Sensitivity	65.95	38.33	41.79	40.78	27.84
Specificity	72.01	89.92	83.05	84.67	90.28
$1 - P(C\|S)$	61.05	64.25	67.05	68.49	67.82
QPS	0.28	0.19	0.25	0.22	0.22

Source: authors' computations; for the dataset see Appendix A.

allows us to compare the stability in the "out-of-sample relationship" between exchange rates and the two classes of fundamentals identified by the original KLR EWI (a mixture of real and financial variables) and by the pseudo-financial EWI (more focused on financial variables).

Table 10 reports the results for the in-sample detection of a structural break. The analysis is based on the approach of Berg and Pattillo (1999) and evaluates the significativeness of four most relevant variables (i.e. the real exchange rate, international reserves, exports and M2/reserves) in predicting the crisis by means of a probit model where the dependent variable is the occurrence of the crisis 24 months ahead.

The first column in Table 10 reports the estimates for the full sample (i.e. 37 countries in the period 1970:1-2010:1) and shows that three out of four variables (all except M2/Reserves) are statistically significant at the standard 5-per-cent level. In column (2) the dummy variables single out the original KR sample (20 countries in 1970:1-1995:12) and allows us to test whether there is a significant difference. Besides the intercept, only M2/Reserves results significantly positive. This could be related to the large incidence of crises in fixed exchange-rate regimes in the pre-1995 period.

Column (3) of Table 10 checks the difference between the full sample and the sample containing only the new added 17 countries for the whole time period 1970-2009. Again, besides the intercept and M2/Reserves, all the other variables are not significantly different at the 5-per-cent level. Hence, both the original KR sample and the sole restriction to the new 17 countries for the whole time period 1970-2009 cannot make us conclude for a structural break.

Instead, when checking the difference of the last subperiod 2005-2009 for all the countries, indications of a significant break cannot be excluded. Indeed, the last column (4) in Table 10 shows a significant difference in all the parameters at the 5-per-cent level (except for M2/Reserves, significant at 10 per cent). Moreover, when looking at the LR test, although they always reject the null hypothesis of same parameters, in the case of column (4) the LR statistics is much greater than in all the other cases.

Hence, we may conclude for higher instability in the sample after 2005.

Our second test for instability hinges on the out-of-sample performance of the original KLR indicator for the period 2006-2009.

Table 11 reports the usual indexes for both the KLR and the pseudo-financial indicator in predicting the Asian currency crises in 1995:4-1997:12 and the currency crises during the period of the Great Recession, 2006:1-2010:1 (signaling threshold is 25 per cent).

Regarding the performances of the two EWI for the period of the Asian crisis, similarly to the in-sample exercise, the percentages remain high for the correctly called periods of either crisis or tranquility. The relatively good performance of both indicators is pointed out by the

Table 10: Probit estimates. Full sample, indicators in percentile

VARIABLES	(1)	(2)	(3)	(4)
Real exchange rate	-0.713***	-0.745***	-0.736***	-1.237***
	(0.0542)	(0.0617)	(0.0612)	(0.0668)
Reserves	-0.488***	-0.557***	-0.577***	-0.539***
	(0.0800)	(0.0872)	(0.0862)	(0.0893)
Exports	-0.378***	-0.418***	-0.446***	-0.496***
	(0.0569)	(0.0642)	(0.0634)	(0.0658)
M2/Reserves	-0.110	-0.293***	-0.222***	-0.338***
	(0.0769)	(0.0854)	(0.0840)	(0.0893)
D KR sample		-0.918***		
		(0.120)		
dKR*RER		0.244*		
		(0.138)		
dKR*Res		0.251		
		(0.230)		
dKR*Exp		0.139		
		(0.146)		
dKR*M2/Res		0.926***		
		(0.211)		
D new sample			-0.833***	
			(0.125)	
dNS*RER			0.175	
			(0.144)	
dNS*Res			0.431*	
			(0.246)	
dNS*Exp			0.283*	
			(0.150)	
dNS*M2/Res			0.596***	
			(0.223)	
D forecast				-1.207***
				(0.139)
dF*RER				1.611***
				(0.139)
dF*Res				0.497**
				(0.229)
dF*Exp				0.648***
				(0.141)
dF*M2/Res				0.374*
				(0.209)
Constant	-0.239***	-0.0617	-0.0852	0.0755
	(0.0465)	(0.0526)	(0.0519)	(0.0529)
LR tests		85.47***	60.27***	321.30***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: authors' computations; for the dataset see Appendix A.

Table 11: Out-of-Sample Performance of the KLR EWI and the Pseudo-Financial EWI for the 1997 Asian Crisis and the Great Recession (2006-2009) (signalling probability $\tau = 25$; all methods)

1997 Asian Crisis					
	KLR	BP Linear	BP piecewise	Probit KLR	Sieve NLLS
KLR EWI					
Correctly called	78	68.99	64.60	66.67	72.73
Sensitivity	32	25.78	18.62	51.57	22.64
Specificity	87	83.12	76.54	71.46	88.62
$1 - P(C\|S)$	66	66.66	82.92	63.56	61.29
QPS	0.26	0.34	0.37	0.26	0.38
Pseudo-Financial EWI					
Correctly called	84.11	69.23	66.14	75.15	65.15
Sensitivity	7.42	28.87	18.30	25.79	28.93
Specificity	99.31	82.56	76.44	90.82	76.65
$1 - P(C\|S)$	31.81	64.66	85.66	52.87	71.78
QPS	0.27	0.36	0.36	0.34	0.36
Great Recession (2006-2009)					
	KLR	BP Linear	BP piecewise	Probit KLR	Sieve NLLS
KLR EWI					
Correctly called	69	75.12	72.96	74.46	75.79
Sensitivity	8	10.81	8.11	4.99	11.44
Specificity	84	91.82	89.79	90.56	90.69
$1 - P(C\|S)$	88	74.47	82.91	89.10	77.84
QPS	0.33	0.37	0.37	0.33	0.37
Pseudo-Financial EWI					
Correctly called	80.30	79.91	74.29	81.19	77.61
Sensitivity	1.17	5.80	6.70	0.00	8.50
Specificity	98.64	95.87	88.85	100	93.61
$1 - P(C\|S)$	83.33	76.79	88.55	-	76.42
QPS	0.32	0.31	0.33	0.32	0.37

sum, greater than one, of Sensitivity and Specificity. Sensitivity is comparatively low with respect to the in-sample results, but still appreciable since a crisis is correctly anticipated on average, across all the methods, with 30 per cent probability for the KLR EWI and 21 per cent for the pseudo-financial EWI.

It ought to be noticed that for the Asian crisis, the KLR method performs best among all techniques when using the original KLR EWI, while it worsens when considering the pseudo-financial EWI. This is not surprising, since it uses only 4 variables that makes the mapping from the composite indicator to the probability space more troublesome. Instead, when the mapping is done through the probit specification (i.e. KLR Probit), the performance of the pseudo-financial EWI is comparable with the other methods.

Overall the two EWIs have very similar performances, hence indicating that there is no big gain when focusing on the core pseudo-financial variables. The only exception is the average probability of anticipating a crisis, $P(C|S)$, that reveals a better average performance of the pseudo-financial indicator (31 per cent versus 40 per cent on average).

The same conclusions cannot be drawn when considering the out-of-sample performance for the period of the Great Recession (2006-2009), as reported in the lower part of Table 11. Although the probability of "correctly-called" periods does not drop, the sum of Sensitivity and Specificity falls and is not always greater than one across all methods. There is a relevant decrease also in probability of correctly signalling a crisis, $P(C|S)$, for both indicators. The pseudo-financial EWI with the Sieve NLLS method is the best performing indicator.

In conclusion, no large difference is detected and both indicators have become much less reliable during the Great Recession. Hence, we interpret this result as evidence of the instability in the relationship between exchange rates and fundamentals in the latter period that does not vanish when restricting the core of fundamentals to the pseudo-financial variables.

Finally, Figure 1 shows the out-of-sample conditional probabilities of all the currency crises during the Great Recession for all the countries of our sample when using both the Sieve NLLS and original KLR methods. We notice that the original KLR EWS correctly signals a crisis only for seven countries (a signal inside the shaded area is issued for Poland, Hungary, Venezuela, Korea, Serbia, Norway, Slovak Republic), while a false alarm is issued for all the other countries. Figure 2 reports for comparison the same exercise for the Asian Crisis.

Figure 1 highlights the occurrence of a contemporaneous rise in probabilities of a crisis (that is, a signal) in 32 countries (when considering both methods), although only 7 of them were considered currency crises according to our definition. Such contemporaneous rise occurs in the time span between the last quarter of 2008 and the first quarter of 2009, which corresponds to a particularly bad period of the global financial crisis: Lehman Brothers collapsed in September 2008 and the world stock markets bottomed in March 2009.

We summarize this qualitative result in Table 13, where we ordered countries according to the out-of-sample indications coming from: (i) the KLR EWI and using the KLR method to obtain the conditional probability of a crisis, (ii) the pseudo-financial EWI with the Sieve NLLS method for the probability derivation. We choose these two methods coupled with the relative EWIs because the Sieve NLLS is the best in the in-sample experiment and his performance is good enough in out-of-sample forecast. KLR instead is a natural benchmark in the EWS literature.[12]

The Sieve NLLS issues a good signal only for three crises, but it has the lowest number of false alarms among all the methods. The group of countries that experienced a crisis but for which no signal was issued had some relevant currency swings. This is a clear indication that macroeconomic fundamentals have lost their predictive power in the latter period.

The KLR method instead is able to issue an early warning in Venezuela, Korea, Iceland, Poland, Norway and a late warning for Denmark, Sweden and Croatia. Indeed, even if the NLLS method is able to provide a better fit in aggregate[13], KLR may be more interesting from a qualitative point of view even though it is less reliable because of the high quantity of false alarms.

Regarding the performance of the two methods in forecasting the Asian crisis, a summary is provided in table 12. As it has been noted before, KLR has the best out-of-sample performance; as we can see from the table, it issued a signal for *all* the countries that had a crisis, though at the cost of of a slightly higher number of false signals compared to other methods. However, from a qualitative perspective, the two methods do not differ very much.

[12]Similar tables for all the other methods and EWIs are available upon request. In particular, in the literature BP linear is the other traditional benchmark. NLLS performs better than BP linear because of less false alarms and because it signals for a longer time when the signal is good. We should note however that BP linear probit is qualitatively similar to Sieve NLLS.

[13]Our explanation for such a feature of the Sieve approach depends on the fact that it is smoother in the variables and hence it produces a higher degree of autocorrelation of the fitted probabilities. So, when it issues a good signal, usually it keeps signalling for a longer time, enhancing the sensitivity and thus boosting the overall goodness of fit. Clearly this depends on the limitations of the classification table for binary variables in a time-series context.

Figure 1: Out-of-Sample Probability of Currency Crisis for the Great Recession: BP linear EWS (blue line) and KLR EWS (original method for the construction of the probability distribution; black line)

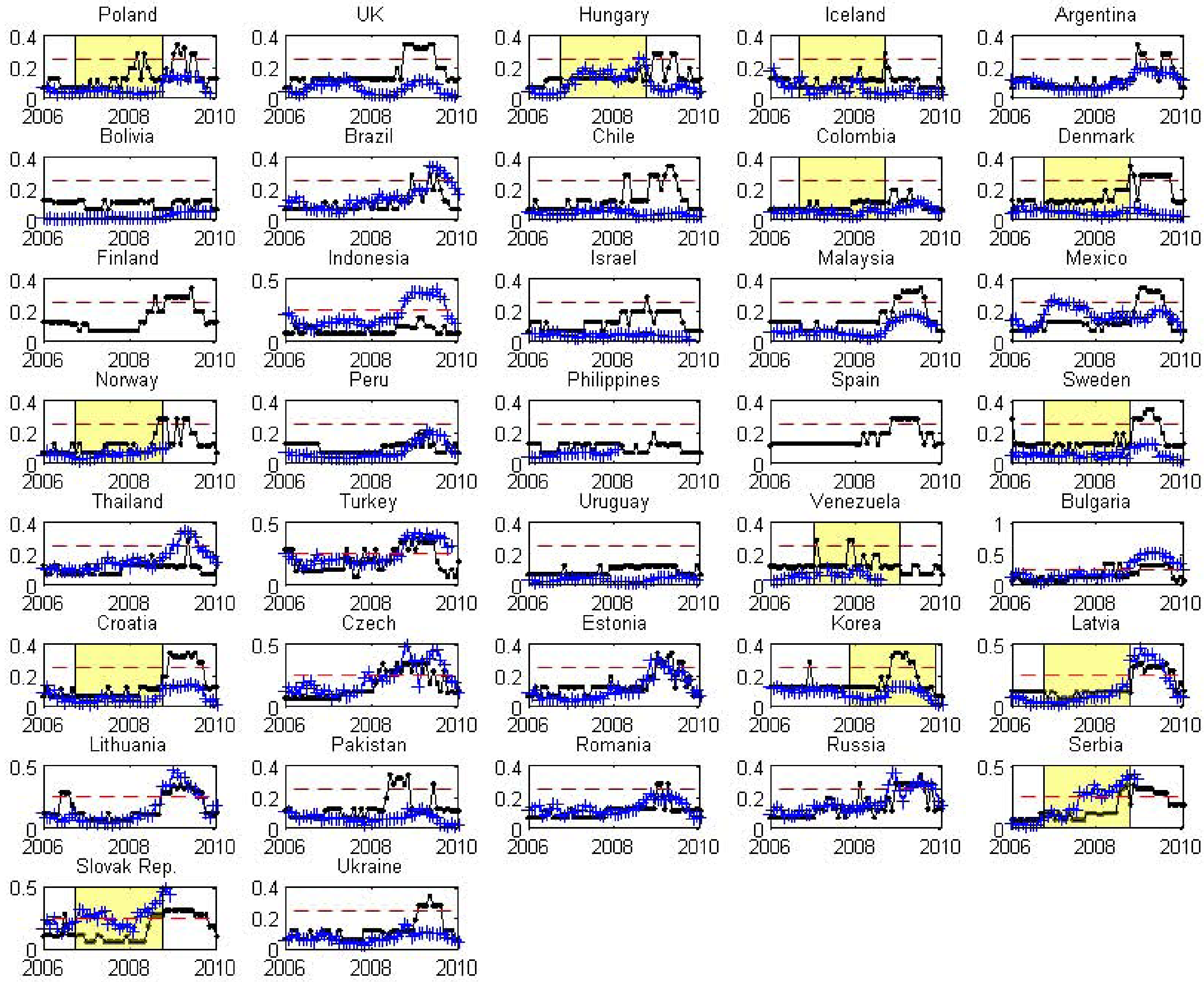

Figure 2: Out-of-Sample Probability of Currency Crisis for the Asian Crisis: BP linear EWS (blue line) and KLR EWS (original method for the construction of the probability distribution; black line)

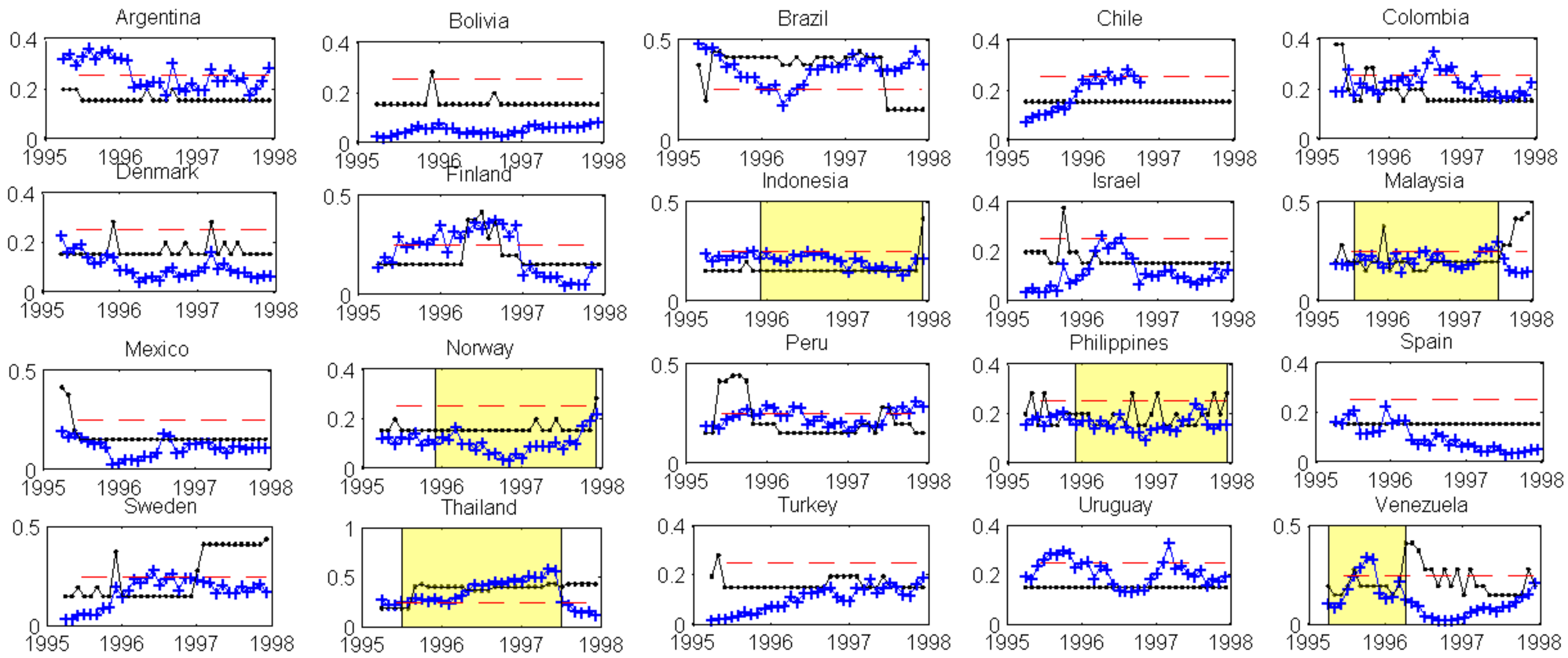

Table 12: Out-of-Sample summary table for the Great Recession

	Crisis (Date of crisis; date of 1st signal)	No Crisis
	KLR EWI with KLR method	
Signal	DEN (2008-10; 2008-10), NOR (2008-10; 2008-09), VEN (2009-01; 2007-02), ICE (2008-09; 2008-09), KOR (2008-11; 2006-12), POL (2008-10; 2008-03), SER (2008-10; 2008-07), SLO (2008-10; 2006-07)	ARG (2008-12), BRA (2008-12) CHI (2008-04), FIN (2008-08), ISR (2008-10), MAL (2008-12), MEX (2008-12), SPA (2008-11), THA (2009-05), TUR (2006-01), BUL (2008-03), CZE (2008-03), EST (2009-01), LIT (2006-06), PAK (2008-06), ROM (2009-01), RUS (2008-02) UKR (2009-02) UNK (2008-10)
No signal	COL (2008-09) CRO (2008-10) HUN (2008-10) SWE (2008-10) LAT (2008-10)	BOL, IND, PER, PHI, URU
	Pseudo-financial EWI with Sieve NLLS	
Signal	LAT (2008-10; 2008-10) SER (2008-10; 2007-08) SLO (2008-10; 2006-11)	IND (2008-09) TUR (2007-02), BUL (2008-03), CZE (2007-11), EST (2008-11) LIT (2008-09), RUS (2008-06)
No signal	COL (2008-09), DEN (2008-10) NOR (2008-10), SWE (2008-10) VEN (2009-01), CRO (2008-10) HUN (2008-10), ICE (2008-09) KOR (2008-11), POL (2008-10)	ARG, BOL, BRA, CHI, FIN, ISR, MAL, MEX, PER, PHI, SPA, THA, URU PAK, ROM, UKR, UNK

9 Conclusions

In this paper we have used an extension of the original KLR data set of currency crises to evaluate whether there has been a change in both in-sample and out-of-sample performance especially for the last period of the Great Recession.

Besides a simple extension of the original KLR EWS, we propose two ways of improving its performance. First, we consider both a parametric extension of the original KLR method and a semi-parametric method to construct the conditional probability distribution of the composite indicator. Second, we propose an alternative composite indicator where we restricted the number of macroeconomic variables to four most relevant and better-performing pseudo-financial variables (domestic credit/GDP, the real exchange rate, international reserves and the real interest-rate differential).

Table 13: Out-of-Sample summary table for the Asian Crisis.

	Crisis (Date of crisis; date of 1st signal)	No Crisis
	KLR EWI with KLR method	
sig	MAL (1997-06; 1995-02), NOR (1997-11; 1997-11), PHI (1997-11; 1995-02), THA (1997-06; 1995-08), VEN (1995-11; 1995-07)	BOL (1995-11), ISR (1995-09), BRA (1995-01), MEX (1996-01), COL (1995-01), PER (1995-04), DEN (1995-11), SWE (1995-11), FIN (1996-04), TUR (1995-02), IND (1997-11)
non sig	-	ARG, CHI, SPA, URU.
	Pseudo-financial EWI with Sieve NLLS	
sig	NOR (1997-11; 1997-11), THA (1997-06; 1995-01), VEN (1995-11; 1995-07)	ARG (1995-01), PER (1995-01), BRA (1995-01), SWE (1996-05), COL (1995-01), TUR (1997-10), FIN (1995-06) URU (1995-07) MEX (1995-01)
non sig	MAL (1997-06), PHI (1997-11).	BOL, CHI, DEN, IND, ISR, SPA

The results show that, independently on the method to obtain the probability distribution of the composite indicator and no matters whether using the original composite indicator or the restricted pseudo-financial indicator, currency crises in the last period 2006-2009 have become much more unpredictable than before, especially with respect to the period of the Asian crisis. This occurs when performing both in-sample and out-of-sample exercises.

These results pave the way to future research, which should identify the reasons why such indicators have failed recently. From Figure 1 we notice that for 27 countries, two of the methods we propose signal the occurrence of a crisis in the period that comprehends the last quarter of 2008 and the first quarter of 2009 (the climax of the world financial crisis), although a currency crisis identified by the market-pressure index is detected for only seven countries. This contemporaneous increase in the probability of a crisis suggests that one possible explanation is the occurrence of a common shock and the presence of contagion effects. Future work should head towards testing this hypothesis.

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APPENDIX

A Description of the Data

Sample period: January 1970–January 2010.

Selected Countries

Original KR Countries: Argentina, Bolivia, Brazil, Chili, Columbia, Denmark, Finland, Indonesia, Israel, Malaysia, Mexico, Norway, Peru, Philippines, Spain, Sweden, Thailand, Turkey, Uruguay, Venezuela.

New Added Countries (whole sample period unless indicated): Bulgaria (1990-), Croatia, Czech Republic (1990-), Estonia (1990-), Hungary (1990-), Iceland, South Korea, Latvia (1990-), Lithuania (1990-), Pakistan, Poland (1990-), Romania (1990-), Russia (1990-), Slovak Republic (1990-), Ukraine, United Kingdom.

Macroeconomic Indicators

Indicators with the symbol * are 12-month percent change, otherwise they are in levels.

- *M2 Multiplier**: M2/Base Money
- *Domestic Credit/GDP**: Domestic Credit/GDP. Domestic credit is deflated using CPI. Monthly GDP is obtained by linear interpolation of annual data.
- *Real Interest Rate*: $r_t = \frac{1+i_t}{1+\pi_t} - 1$, where i_t is the deposit rate and π_t is the 12 month CPI inflation rate.
- *Lending/Deposit Rate Ratio*: Lending rate/ deposit rate
- *Excess M1 Balances*: calculated for each country as the residual from a linear regression of the type $M_t/P_t = \beta_0 + \beta_1 t + \beta_2 Y_t + \beta_3 i_t + u_t$, where t is a linear trend, Y_t is monthly real GDP (interpolated linearly) and i_t is the deposit rate.
- *M2/Reserves Ratio**: M2/Reserves. M2 is converted in US dollars using monthly exchange rates.
- *Bank Deposits**: Bank deposits are daflated using CPI

- *Exports**
- *Terms of Trade*: unit value of exports/ unit value of imports
- *Real Exchange Rate*: since not all real appreciations are sympthoms of disequilibrium, deviations from a linear trend are used as indicator.
- *Imports**
- *International Reserves**
- *Real Interest Rate Differential*: is the difference between real deposit rate in the domestic country and the foreign country (US or Eurozone/Germany).
- *Output**: monthly industrial production indices are used.
- *Stock Prices**: stock indices.
- *Deficit*: cash surplus / nominal GDP. Monthly GDP and monthly deficits are obtained by linear interpolation of annual data.

Data Sources

Most of the data are obtained from the online version of the *International Financial Statistics* (IFS) of the IMF.

CPI: IFS line 64.
FX: national currency per US Dollars (end of period) IFS line AE.
RESERVES: Total reserves minus gold (USD). IFS line 1L.
M2: generally 59MB / Croatia, Philippines: IFS line 34 (Transferable deposits) + 35 (other deposits).
BASE MONEY: IFS line 19MA or (Bulgaria, Finland, Korea, Latvia, Serbia) IFS line 14.
IPI: IFS line 66, IFS line 66aa index of output of primary commodities as alternative and industrial employment index for Russia and Ukraine IFS line 67.
STOCK PRICES: IFS line 62 Share Price Index (end of period).
EXPORTS: IFS line 70. The unit of account changes depending on the country: Croatia USD, Bulgaria Leva, Argentina USD, Bolivia USD, Brazil USD, Chile USD, Colombia USD, Finland Markkaa/Euro, Indonesia USD, Norway Kroner, Malaysia Ringgit, Peru USD, Phillipines Pesos, Sweden Kronor, Thailand Bath, Denmark Kroner, Czech Republic Koruny, Estonia Kroony, Hungary Florint, Iceland Kronur, Korea USD, Latvia Lats, Lithuania Litai,

Pakistan Rupees, Poland Zloty, Romania USD, Russia USD, Serbia Dinars, Slovak Republic Koruny/Euro, Ukraine USD, UK Pounds, Turkey USD, Venezuela Bolivares.
IMPORTS: IFS line 71 (unit-of-account currencies as for Exports).
TERMS OF TRADE: unit value of exports (IFS line 74) over unit value of imports (IFS line 75).
LENDING RATE: 60P. Finland: line 60P until 2002M12. Average of lines 60pns, 60phm, 60phn, 60pcs. Poland spa: 60phm,pcs,pcn
DEPOSIT RATE: 60L England: Bank of England: Monthly average of Sterling certificates of deposit interest rate, 3 months, mean offer/bid.
GDP: GDP at current prices line 99B. Monthly data obtained with linear interpolation.
GDP DEFLATOR: annual, 2005 = 100 line 99BIPZF.
DEFICIT: Cash Surplus/Deficit [1-2-31=1-2M] line CSD.
REER: generally IFS line RE (Real exchange rate index based on relative CPI). When it is not available, we built a real exchange rate index (in base 2005=100) based on relative CPI with the US, or with Germany for European countries.
M1: IFS line 59 (national definition) or line 34 (demand deposit).

B Dating the Crises

Table 14: Crisis dates according to different thresholds

Countries	Fixed	Moving threshold	Rolling threshold	Separate samples (1970:1-1981:12 and 1982:1-2010:1)
Argentina	Mar-75	Mar-75	Mar-75	Mar-75
	Jun-75	Jun-75	Jun-75	Jun-75
	Jul-82	Jul-82	Jul-82	Jul-82
	Apr-89	Apr-89	Apr-89	Apr-89
	Dic-89	Dic-89	Dic-89	Dic-89
	Feb-90	Feb-90	Feb-90	Feb-90
	-	Mar-95	-	-
	-	Jul-01	-	-
	-	Jan-02	-	Jan-02
	-	Feb-02	-	Feb-02
	-	Mar-02	-	Mar-02
	-	-	-	May-02

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	-	-	-	Jan-06
Bolivia	Oct-72	Oct-72	Oct-72	Oct-72
	-	Nov-79	-	-
	Feb-82	Feb-82	Feb-82	Feb-82
	Sep-85	Sep-85	Sep-85	Sep-85
	-	Feb-03	-	Feb-03
	-	Oct-08	-	Oct-08
Brazil	-	Jan-74	-	-
	Dic-79	Dic-79	Dic-79	Dic-79
	Sep-82	Sep-82	Sep-82	Sep-82
	Jan-83	-	Jan-83	-
	Feb-83	Feb-83	Feb-83	-
	Mar-90	Mar-90	Mar-90	Mar-90
	-	Oct-97	-	-
	-	Sep-98	Sep-98	-
	Jan-99	Jan-99	Jan-99	Jan-99
	Sep-02	-	-	-
	-	Sep-08	-	-
Chile	Jul-71	Jul-71	Jul-71	Jul-71
	Sep-72	-	-	-
	-	Jun-82	-	-
	Jul-85	Jul-85	Jul-85	Jul-85
	-	Oct-95	-	-
	-	Jun-99	-	-
	-	Oct-08	-	Oct-08
Colombia	-	-	-	Sep-74
	-	Jan-84	-	-
	-	-	Jan-85	-
	-	Aug-95	Aug-95	-
	-	Aug-07	Aug-07	-

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	Sep-08	Sep-08	Sep-08	Sep-08
Denmark	Oct-08	Oct-08	Oct-08	Oct-08
Finland	-	Jul-75	Jul-75	-
	-	-	Nov-78	Nov-78
	-	-	Oct-82	Oct-82
	-	-	May-86	-
	Mar-91	Mar-91	Mar-91	-
	Sep-92	-	Sep-92	Sep-92
Indonesia	Nov-78	-	Nov-78	Nov-78
	-	Mar-83	-	Mar-83
	-	Apr-83	-	Apr-83
	Sep-86	Sep-86	Sep-86	Sep-86
	-	Aug-97	-	-
	-	Oct-97	-	-
	-	-	Dic-97	-
	Jan-98	Jan-98	Jan-98	Jan-98
	May-98	-	-	-
	Jun-98	-	Jun-98	Jun-98
	-	Oct-08	-	-
Israel	Aug-71	Aug-71	Aug-71	Aug-71
	Nov-74	Nov-74	Nov-74	Nov-74
	Sep-75	-	-	-
	Nov-77	Nov-77	Nov-77	Nov-77
	-	Aug-83	-	-
	-	Oct-08	-	Oct-08
Malaysia	-	Dic-92	-	-
	Jul-97	Jul-97	Jul-97	Jul-97
	Aug-97	-	Aug-97	Aug-97
	Dic-97	-	Dic-97	Dic-97

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	Jan-98	Jan-98	Jan-98	Jan-98
	-	Oct-08	-	-
Mexico	Sep-76	Sep-76	Sep-76	Sep-76
	Oct-76	-	Oct-76	-
	-	Jun-81	-	-
	-	Sep-81	-	-
	Feb-82	Feb-82	Feb-82	Feb-82
	Dic-82	Dic-82	Dic-82	Dic-82
	Dic-94	Dic-94	Dic-94	Dic-94
	-	-	-	Aug-98
	-	Oct-08	-	Oct-08
Norway	Nov-78	Nov-78	Nov-78	Nov-78
	-	-	Jan-81	-
	May-86	May-86	May-86	May-86
	Mar-91	Mar-91	Mar-91	-
	Nov-92	-	Nov-92	Nov-92
	Dic-97	Dic-97	Dic-97	Dic-97
	Oct-08	Oct-08	Oct-08	Oct-08
Peru	Jun-76	Jun-76	Jun-76	Jun-76
	Oct-87	Oct-87	Oct-87	Oct-87
	Dic-87	Dic-87	Dic-87	Dic-87
	Sep-88	Sep-88	Sep-88	Sep-88
	-	Aug-05	-	-
	-	-	-	Oct-08
Philippines	Feb-70	Feb-70	Feb-70	Feb-70
	-	Jul-75	-	-
	-	Jan-82	-	-
	-	Nov-82	-	-
	-	-	Sep-83	-
	Oct-83	Oct-83	Oct-83	Oct-83

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	Jun-84	Jun-84	Jun-84	Jun-84
	Feb-86	-	-	-
	-	Jul-97	-	Jul-97
	-	Sep-97	-	Sep-97
	Dic-97	Dic-97	Dic-97	Dic-97
	-	-	-	Oct-00
	-	Oct-08	-	-
Spain	-	Feb-76	Feb-76	-
	-	-	Mar-80	-
	-	Mar-91	Mar-91	-
	Sep-92	Sep-92	Sep-92	Sep-92
	Oct-92	-	Oct-92	-
	Nov-92	-	Nov-92	Nov-92
	-	Dic-98	-	Dic-98
Sweden	-	Aug-77	Aug-77	Aug-77
	Nov-92	Nov-92	Nov-92	Nov-92
	Oct-08	Oct-08	Oct-08	Oct-08
Thailand	-	Nov-78	Nov-78	Nov-78
	-	Oct-79	Oct-79	-
	-	-	Jul-81	Jul-81
	-	-	-	Feb-85
	-	-	-	Oct-85
	-	May-97	-	-
	-	-	-	-
	Jul-97	Jul-97	Jul-97	Jul-97
	Aug-97	Aug-97	Aug-97	Aug-97
	-	-	Nov-97	-
	Dic-97	-	Dic-97	Dic-97
	Jan-98	-	Jan-98	Jan-98
Turkey	Aug-70	Aug-70	Aug-70	Aug-70

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	-	Oct-76	-	-
	Mar-78	Mar-78	Mar-78	-
	Jan-80	-	Jan-80	-
	Feb-80	Feb-80	Feb-80	Feb-80
	Feb-94	Feb-94	Feb-94	Feb-94
	Mar-94	-	Mar-94	Mar-94
	Apr-94	Apr-94	Apr-94	Apr-94
	-	-	-	Feb-01
	Mar-01	Mar-01	Mar-01	Mar-01
	Apr-01	-	-	Apr-01
	-	Oct-08	-	Oct-08
Uruguay	Mar-72	Mar-72	Mar-72	Mar-72
	Nov-82	Nov-82	Nov-82	Nov-82
	Dic-82	Dic-82	Dic-82	Dic-82
	-	-	-	Nov-84
	-	Feb-02	-	-
	-	-	-	Jun-02
	Jul-02	Jul-02	Jul-02	Jul-02
	-	Sep-08	-	-
Venezuela	Feb-84	Feb-84	Feb-84	Feb-84
	Dic-86	Dic-86	Dic-86	Dic-86
	Mar-89	Mar-89	Mar-89	Mar-89
	May-94	May-94	May-94	-
	Dic-95	Dic-95	Dic-95	-
	Apr-96	Apr-96	Apr-96	Apr-96
	Feb-02	Feb-02	Feb-02	Feb-02
	-	Jan-03	-	Jan-03
	-	Apr-07	-	-
	Jan-09	Jan-09	Jan-09	Jan-09
Bulgaria	-	-	Jan-94	-
	Jul-94	-	-	-

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	-	-	-	Jan-96
	-	-	-	Mar-96
	-	-	-	May-96
	-	-	-	Jul-96
	-	Oct-08	-	-
Croatia	-	-	Feb-95	-
	Oct-08	Oct-08	Oct-08	Oct-08
	Jan-09	Jan-09	Jan-09	Jan-09
Czech	-	-	Feb-93	-
	-	Aug-08	-	-
	-	Oct-08	-	-
	-	Jan-09	-	Jan-09
Estonia	-	-	Jul-92	-
	-	-	-	Jan-09
Hungary	-	-	Sep-89	-
	Oct-08	Oct-08	Oct-08	Oct-08
	Jan-09	Jan-09	Jan-09	Jan-09
Iceland	-	Dic-72	-	-
	Sep-74	Sep-74	Sep-74	Sep-74
	Feb-75	Feb-75	Feb-75	Feb-75
	Aug-82	Aug-82	Aug-82	Aug-82
	May-83	May-83	May-83	May-83
	Sep-08	-	Sep-08	Sep-08
	Oct-08	-	Oct-08	Oct-08
Korea	-	Jun-71	-	-
	-	Dic-71	-	-
	Jan-80	Jan-80	Jan-80	Jan-80
	Nov-97	Nov-97	Nov-97	Nov-97

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
	Dic-97	Dic-97	Dic-97	Dic-97
	-	Sep-08	-	-
	Nov-08	Nov-08	Nov-08	-
Latvia	-	-	Feb-94	-
	Oct-08	Oct-08	Oct-08	Oct-08
	-	-	Nov-08	-
	Jan-09	-	Jan-09	Jan-09
Lithuania	-	-	Jan-93	-
Pakistan	May-72	May-72	May-72	May-72
	-	-	-	Oct-96
	-	Mar-08	-	-
	-	May-08	-	-
	-	Aug-08	-	-
Poland	Jul-86	-	Jul-86	-
	May-89	-	-	May-89
	-	Mar-05	-	-
	Oct-08	Oct-08	Oct-08	Oct-08
	Jan-09	-	Jan-09	Jan-09
Romania	-	-	Feb-79	-
	May-89	May-89	May-89	-
	Aug-89	Aug-89	Aug-89	Aug-89
	Feb-90	-	Feb-90	Feb-90
	Nov-90	-	Nov-90	Nov-90
	-	Jan-97	-	Jan-97
	-	-	-	Feb-97
	-	-	-	Nov-99
	-	Oct-08	-	-
	-	Jan-09	-	-

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Countries	Fixed	Moving threshold	Rolling threshold	Two samples
Russia	-	-	Jul-96	-
	Aug-98	-	Aug-98	Aug-98
	Sep-98	Sep-98	Sep-98	Sep-98
	-	Oct-08	-	-
	-	Jan-09	-	-
Serbia	-	-	Jan-02	-
	Oct-08	Oct-08	Oct-08	Oct-08
	Jan-09	-	Jan-09	Jan-09
Slovak Rep.	-	-	Feb-93	-
	Oct-08	Oct-08	Oct-08	Oct-08
Ukraine	-	-	Jan-93	-
	Mar-93	-	-	-
	Dic-93	-	-	-
	Jun-94	Jun-94	Jun-94	Jun-94
	Oct-94	-	-	-
	-	-	-	Sep-98
	-	Oct-08	-	Oct-08
	-	Nov-08	-	Nov-08
	-	Dic-08	-	-
UK	-	Jul-72	Jul-72	-
	Sep-92	-	-	Sep-92
	Oct-92	-	-	Oct-92
	-	Jan-97	-	Jan-97
	-	Aug-08	-	Aug-08
	-	Oct-08	-	Oct-08