WP/13/134

IMF Working Paper

Comparing Parametric and Non-parametric Early Warning Systems for Currency Crises in Emerging Market Economies

Fabio Comelli

INTERNATIONAL MONETARY FUND

 WP/13/134

IMF Working Paper

IMF Institute for Capacity Development

Comparing Parametric and Non-parametric Early Warning Systems For Currency Crises in Emerging Market Economies

Prepared by Fabio Comelli [1]

Authorized for distribution by Marc Quintyn

May 2013

Abstract

The purpose of this paper is to compare in-sample and out-of-sample performances of three parametric and non-parametric early warning systems (EWS) for currency crises in emerging market economies (EMs). The parametric EWS achieves superior out-of-sample results compared to the non-parametric EWS, as the total misclassification error of the former is lower than that of the latter. In addition, we find that the performances of the parametric and non-parametric EWS do not improve if the policymaker becomes more prudent. From a policy perspective, the policymaker faces the standard trade-off when using EWS. Greater prudence allows the policymaker to correctly call more crisis episodes, but this comes at the cost of issuing more false alarms. The benefit of correctly calling more currency crises needs to be traded off against the cost of issuing more false alarms and of implementing corrective macroeconomic policies prematurely.

JEL Classification Numbers: F31, F37

Keywords: Early warning systems, emerging markets.

Author's E-Mail Address: fcomelli@imf.org

[1] Comments from Suman Basu, Bertrand Candelon, Alina Carare, Gaston Gelos and Marc Quintyn are gratefully acknowledged.

Contents

I. Introduction

The goal of this study is to compare how parametric and non-parametric early warning systems (EWS) predict in-sample and out-of-sample currency crises in emerging market economies (EMs). We look at episodes of currency crises that took place in selected EMs between January 1995 and December 2011. We define currency crises as large depreciations of the nominal exchange rate and/or extensive losses of foreign exchange reserves over a 24-month forecast horizon. In this context, a crisis occurs when the exchange market pressure index - a weighted average of one-month changes in the exchange rate and foreign exchange reserves - is more than three (country-specific) standard deviations above the country average value.[2]

We build parametric and non-parametric EWS. In the parametric EWS a binary crisis variable is regressed on a set of explanatory macroeconomic indicators and an indicator of political risk, using a fixed effects logit estimator, to estimate the probability of experiencing a currency crisis. We build the non-parametric EWS following IMF (2013) and Dabla-Norris and Bal Gündüz (2012). In the non-parametric EWS the crisis probability has been derived as a weighted average of crisis signals issued by a set of indicators. In both approaches, we use a panel dataset which includes macroeconomic and political risk indicators for 28 EMs, with monthly data between January 1995 and December 2011. As is standard in the EWS literature, we are interested in assessing the in-sample and out-of-sample performances of the parametric and non-parametric EWS.

This study contributes to the EWS existing literature in the following ways. First, we assess in-sample and out-of sample performances of parametric and non-parametric EWS by calculating *optimal* cut-off values for the crisis probabilities, while in most studies those cut-off values are selected arbitrarily. As noted by Candelon and others (2012), this matters because the cut-off value for the crisis probability determines the total misclassification error of an EWS.[3] Selecting cut-off values arbitrarily implies that the quantification of the total misclassification error is also arbitrary. Second, we allow for the possibility that the policymaker's policy preferences change. Specifically, when selecting the cut-off values for the crisis probability, we first assume that the policymaker is equally concerned about the risk of missing a crisis and that of issuing a false alarm, therefore she will assign the same weight to

[2]See IMF, (2002).

[3]The total misclassification error of an EWS is the sum between the percentages of missed crises and of false alarms issued by the EWS.

both risks. Then, we assume that the policymaker is relatively more concerned about the risk of missing a crisis episode than issuing a false alarm. Therefore she will err on the side of caution and attach a larger weight to the risk of missing crises than to the risk of issuing a false alarm. We do this because we are interested to assess how changing the policymaker's preferences affects in-sample and out-of-sample performances of the parametric and non-parametric EWS. Furthermore, from an empirical point of view, we include in the EWS a specific measure of political risk which quantifies the degree of government instability in a given country, to check whether government instability is significant or not to explain the crisis incidence.

We find that in the parametric EWS, real GDP growth, the ratio between foreign exchange reserves and short term external debt, the growth rate in the stock of foreign exchange reserves, and the current account balance are all significant and negatively related with the crisis incidence. A political risk explanatory variable measuring the degree of government instability and the ratio of domestic money stock expressed in U.S. dollars and foreign exchange reserves are significant and positively related with crisis incidence. By contrast, monthly changes in real effective exchange rates and a measure of real effective exchange rate misalignment were not significant. Similarly, neither credit to the government, nor the level of foreign exchange reserves were significantly associated with crisis incidence. A measure of political risk assessing the presence of corruption in the political system was not significant to explain crisis incidence.

In the non-parametric EWS, the current account balance and the ratio between the stock of foreign exchange reserves and short-term external debt are the two most reliable indicators in issuing crisis signals. Real GDP growth, the change in foreign exchange reserves, the ratio between the domestic money stock expressed in U.S. dollars and foreign exchange reserves, and government instability appear less reliable. All in all, the results obtained with the parametric and non-parametric EWS suggest that monetary expansions, which may reflect rapid increases in credit growth, are expected to increase crisis incidence. Finally, government instability plays is significant in the parametric EWS, but does not play an important role not in the non-parametric EWS.

In terms of performance, the parametric EWS achieves superior out-of-sample results compared to the non-parametric EWS. We also find that the percentages of correctly predicted out-of-sample crisis episodes by two of the three EWS during the period January 2009-December 2011 increase substantially compared to out-of-sample periods that include the year 2008. One possible interpretation of this result is that after 2008, the most turbulent year of the global financial crisis, international investors may have been assigning greater importance to macroeconomic indicators when assessing their exposure toward EMs assets. We also find that the performance of the EWS does not improve when the policymaker is relatively more concerned about the risk of missing a crisis than the risk of issuing a false alarm.

This paper is organized as follows. Section 2 reviews the literature, while section 3 discusses the methodology used in this study. Section 4 presents the results obtained with the parametric and non parametric EWS, while in section 5 we discuss and compare the in-sample and out-of-sample performances of the parametric and non-parametric EWS. Section 6 concludes.

II. Related Literature

Following the episodes of severe financial distress in Mexico (1994-95) and Asia (1997-98), economists became interested in thinking about frameworks that could help policymakers anticipating episodes of financial crises, whose economic costs are well documented (Cerra and Saxena, 2008). We divide the EWS literature contributions relevant for this study in two groups. The first group includes those studies that propose parametric (i.e. regression-based) and non-parametric (i.e. crisis signal extraction) EWS and assess in-sample and out-of-sample performances of different EWS. Kaminsky, Lizondo and Reinhart (KLR) look at the evolution of those indicators which exhibit an unusual behavior in periods preceding financial crises. When the indicator exceeds a given threshold then that indicator is issuing a signal that a crisis could take place within the next 24 months. They find that exports, measures of real exchange rate overvaluation, GDP growth, the ratio between the money stock and foreign exchange reserves and equity prices have the best track record in terms of issuing reliable crisis signals. Berg and Pattillo (1999) test the KLR model out-of-sample and show that their regression-based approach tends to produce better forecasts compared to the KLR model. Bussiere and Fratzscher (2006) develop a multinomial logit regression-based EWS, which allows distinguishing between tranquil periods, crisis periods and post-crisis periods. They show that the multinomial logit model tends to predict better than a binomial logit model episodes of financial crisis in emerging market economies. Beckmann and others (2007) compare parametric and non-parametric EWS using a sample of 20 countries during the period included between January 1970 and April 1995. They find that the parametric EWS tends to perform better than non-parametric EWS in correctly calling financial crisis episodes. However, as noted by Candelon and others (2012), in these studies the choice of the crisis probability cut-off value is arbitrarily made and not optimally derived.

The second group of relevant EWS literature contributions for this study includes recent studies that discuss the significance of the various macroeconomic indicators to explain crisis incidence. Berkmen and others (2012) looked at the change in growth forecasts by professional economists before and after the global financial crisis. They found that countries with more leveraged domestic financial systems and rapid credit growth tended to suffer larger downward revisions to their growth forecasts, while international reserves did not play a significant role. Similarly, Blanchard and others (2010) do not find a significant role played by reserves in explaining in unexpected growth, which is defined as the forecast error for output growth in the semester from October 2008 until March 2009. Rose and Spiegel (2012) find that the only robust predictor of crisis incidence in the 2008 global financial crisis is the size of the equity market prior to the crisis. They are unable to link most of the other commonly cited causes of the global financial crisis to its incidence across countries. By contrast, Gourinchas and Obstfeld (2011) look at financial crisis episodes in advanced and emerging economies from 1973 until 2010. They find that for both advanced and emerging market economies, the two most robust predictors are domestic credit growth and real currency appreciation. In addition, they find that in emerging market economies the country's level of foreign exchange reserves is a significant factor in determining the probability of future crises. Llaudes and others (2010) find that foreign exchange reserve holdings helped to mitigate the growth collapse in EMs provoked by the global financial crisis. Frankel and Saravelos (2012) estimate the crisis incidence of the 2008-2009 global financial crisis. They surveyed the existing literature on early warning indicators to see which leading indicators were the most reliable in explaining the crisis incidence. They find that foreign exchange reserves, the real exchange rate, credit growth, real GDP growth and the current account balance as a percentage of GDP are the most reliable indicators to explain crisis incidence and conclude that the large accumulation of foreign exchange reserves has played an important role in reducing countries' vulnerability during the global financial crisis. The results obtained in this study are in line with the notion that the stock of foreign exchange reserves is significantly negatively related with out measure of crisis incidence.

Against this background, the contribution of this study to the EWS literature is twofold. First, we assess in-sample and out-of sample performances of parametric and non-parametric EWS by calculating *optimal* cut-off values for the crisis probabilities, while in most of the existing studies those cut-off values are selected arbitrarily. As noted by Candelon and others (2012), this matters because the cut-off value for the crisis probability determines the total misclassification error of an EWS.[4] Selecting cut-off values arbitrarily implies that the quantification of the total misclassification error is also arbitrary. Second, we enrich the EWS literature by letting the policymaker having different policy preferences about the risk of missing a crisis and issuing a false alarm. The role of the policymaker in an EWS is to select the cut-off values for the crisis probability. In this context, we are interested to assess how changing the policymaker's policy preferences affects the EWS performance.

III. Methodology

We build competing EWS to compare their ability to correctly predict in-sample and out-of-sample episodes of currency crises in EMs. We focus on those EMs which had at least once experienced an episode of currency crisis between January 1995 and December 2011.[5] We proceed as follows. We build an exchange rate pressure index from which we derive a crisis variable that identifies episodes of currency crisis in EMs. The crisis variable is binary, as it assumes the value of one if a currency crisis takes place within the next 24 months, and 0 otherwise. Once defined the crisis variable, we construct the parametric and non-parametric EWS. For each EWS, the objective is to construct a crisis probability.

A. Parametric EWS

The parametric EWS is regression-based, where the crisis variable (or crisis incidence) is regressed on a set of selected macroeconomic indicators of emerging market economies, using a fixed effects logit estimator. A crisis probability is then calculated with the coefficient estimates obtained from the regression. Following Bussiere and Fratzscher (2006), we assume that there are N countries, $i = 1, 2, ..., N$, that we observe during T periods $t = 1, 2, ..., T$. For each country and month, we observe a forward-looking crisis variable Y_{it} that can assume as values only 0 (non-crisis) or 1 (crisis). To derive the crisis binary variable, we follow Kaminsky and others (1998) and build an exchange rate pressure index.[6] The exchange rate pressure index for country i at time t ($ERPI_{i,t}$) is defined as a weighted average between the monthly change in the nominal exchange rate and that in the stock of foreign exchange

[4] The total misclassification error of an EWS is the sum between the percentages of missed crises and of false alarms issued by the EWS.

[5] Argentina, Brazil, Bulgaria, Chile, Colombia, Croatia, Egypt, Hungary, India, Indonesia, Kazakhstan, Korea, Lebanon, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Romania, Russia, South Africa, Taiwan, Thailand, Turkey, Ukraine, Uruguay and Vietnam.

[6] For a discussion on exchange rate pressure indices see Eichengreen and others (1995).

reserves.

$$ERPI_{i,t} = \frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}} - \left(\frac{\sigma_{e_i}}{\sigma_{fxr_i}}\right) \frac{fxr_{i,t} - fxr_{i,t-1}}{fxr_{i,t-1}} \tag{1}$$

where $e_{i,t}$ denotes the nominal exchange rate of country i's currency against the U.S. dollar at time t, while $fxr_{i,t}$ denotes the stock of foreign exchange reserves of country i at time t. Finally, σ_{e_i} and σ_{fxr_i} are the standard deviations of the nominal exchange rate and foreign exchange reserves in country i, respectively.

As a next step, we define a currency crisis hitting country i at time t, $CC_{i,t}$, as a binary variable that can assume either 1 (when the ERPI is above its mean by a number of standard deviations) or 0 (otherwise):

$$CC_{i,t} = \begin{cases} 1 & \text{if } ERPI_{i,t} > \overline{ERPI_i} + \phi\sigma_{ERPI_{i,t}} \\ \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

where ϕ is arbitrarily set equal to 3, and $\sigma_{ERPI_{i,t}}$ is the standard deviation of the exchange rate pressure index of country i.[7] Next, the variable $CC_{i,t}$ is converted into the forward-looking crisis variable $Y_{i,t}$ which is defined as follows

$$Y_{i,t} = \begin{cases} 1 & \text{if } \exists\ k = 1, \ldots, 24 \text{ s.t } CC_{i,t+k} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The forward-looking crisis variable $Y_{i,t}$ is equal to 1 if *within* the next 24 months a currency crisis is observed in country i, and to 0 otherwise. As in Bussiere and Fratzscher (2006), the crisis definition adopted in this study allows to capture both successful and non-successful speculative attacks to a given currency.

We define $Pr(Y_{i,t} = 1)$ as the probability of country i to experience a currency crisis at time t. We estimate the probability of a currency crisis with a fixed effects logit model whereby the probability of a currency crisis is a non-linear function of the macroeconomic indicators

[7] See IMF (2002). In the EWS literature, ϕ typically assumes the values of either 2 or 3. The choice of values to assign to ϕ involves a trade-off. When $\phi = 2$, the exchange rate pressure index will identify more crisis episodes, while when $\phi = 3$, the index will identify less crisis episodes.

X:

$$Pr(Y_{i,t} = 1) = F(X\beta) = \frac{e^{X\beta}}{1 + e^{X\beta}} = P_t \tag{4}$$

Condition (4) expresses the unconditional probability that country i experiences a currency crisis at time t as a function of the macroeconomic indicators. To obtain the estimates of β, we regress the crisis binary variable $Y_{i,t}$ on the macroeconomic indicators in the period between January 1995 and December 2007. Then, based on (4), we derive currency crises probabilities.

B. Non-parametric EWS

Following Dabla-Norris and Bal Gündüz (2012) and IMF (2013), in the non-parametric EWS the crisis probability P_t is calculated as a weighted average of crisis signals issued by a set of selected EMs macroeconomic indicators. To establish when an indicator is issuing a crisis signal, we need to choose a threshold. In most of the EWS literature, thresholds are arbitrarily chosen. Instead, like Candelon and others (2012) and IMF (2013), for each indicator we determine an optimal threshold because we want to reduce as much as possible the forecasting error. For instance, suppose that the threshold has been arbitrarily set very high. Suppose also that the indicator assumes a value which is lower than the arbitrarily chosen threshold and that a crisis occurs. In that case, the indicator does not issue a crisis signal, yet a crisis occurs. We refer to this kind of forecasting error as type 1 error (missing a crisis because the threshold has been set too high). Alternatively, suppose that the indicator assumes values which are higher than the threshold, which has been arbitrarily set too low and suppose that a tranquil period follows. In that case, the indicator issues a crisis signal, yet no crisis has materialized. We refer to this forecasting error as type 2 error (issuing a false alarm). In order to minimize the sum of errors associated to a given threshold, for each macroeconomic indicator we choose an optimal threshold. In correspondence of the optimal threshold, the sum between type 1 and type 2 errors (total misclassification error) is minimized. Hence, the threshold is optimal in the sense that it discriminates best between crisis and non-crisis signals. There is no other threshold that, for a given macroeconomic indicator, separates the crisis observations from non-crisis ones better than the optimal threshold. Summing up, choosing an optimal threshold allows minimizing the forecasting errors; this is not possible if instead the threshold is arbitrarily chosen.

To obtain the crisis probability with the non-parametric EWS, we proceed in several steps.

First, for each macroeconomic indicator X_i, we derive an optimal threshold that minimizes the total misclassification error. Specifically, for each indicator X_i we separate the observations assumed by the indicator in the crisis periods from those assumed in the non-crisis periods, into two subsamples. For both subsamples we calculate the cumulative density functions, and the associated total misclassification error, which is given by the sum between type 1 error (missing a crisis) and type 2 error (issuing a false alarm). The optimal threshold X_i^* is chosen such that the total misclassification error z_i associated to X_i is the lowest. Each time when $X_{i,t} \geq X_i^*$,[8] the indicator X_i is issuing a crisis signal at time t.

The total misclassification error is defined as follows:

$$z_i = type\ 1\ error\ (X_i) + type\ 2\ error\ (X_i) \tag{5}$$

where

$$type\ 1\ error\ (X_i) = \frac{total\ missed\ crises\ (X_i)}{total\ crises\ (X_i)}$$

$$type\ 2\ error\ (X_i) = \frac{total\ false\ alarms\ (X_i)}{total\ non-crises\ (X_i)}$$

Second, we need to map indicator values into zero-one scores. To do that, we convert each indicator $X_{i,t}$ into a binary variable $f_{i,t}$: when $X_{i,t}$ assumes values equal to or higher than its optimal threshold X_i^*, a crisis signal is issued and a value of 1 is assigned to $f_{i,t}$:

$$f_{i,t} = \begin{cases} 1 & X_{i,t} \geq X_i^* \\ \\ 0 & otherwise \end{cases}$$

As a next step, we need to choose weights to aggregate crisis signals issued by the indicators into a crisis probability. Specifically, when $f_{i,t} = 1$, the indicator X_i is issuing a crisis signal, and the binary variable $f_{i,t}$ is multiplied by the weight assigned to the indicator X_i. The weight of the indicator X_i is a function of the total misclassification error z_i and is defined as:

$$w_i = \frac{1 - z_i}{z_i} \tag{6}$$

[8] Alternatively, when $X_{i,t} \leq X_i^*$, depending on the indicator.

Intuitively, condition (6) implies that the higher the weight of an indicator X_i, the lower its total misclassification error z_i, hence the higher its reliability in issuing crisis signals. It follows that the more reliable an indicator is, the higher its contribution in calculating the crisis probability should be.

Next, we use the weight w_i to construct the crisis probability for each sector of the economy $\Pi_{j,t}$:

$$\Pi_{j,t} = \sum_{i=1}^{N} w_i f_{i,t} \tag{7}$$

where the subscript $j = 1, 2, ..., J$ denotes the sectors of the economy and where each crisis signal $f_{i,t}$ is multiplied by the weight w_i. Put differently, $\Pi_{j,t}$ is a weighted average of the crisis signals $f_{i,t}$ issued by the macroeconomic indicators of a given sector. The higher $\Pi_{j,t}$, the higher the probability that a crisis will originate from sector j, hence the higher the contribution of sector j to the likelihood of experiencing a currency crisis. The sectors of the economy that we consider are the external sector, the domestic sector and the financial sector.

Finally, we aggregate the sectoral crisis probability $\Pi_{j,t}$ into a measure of crisis probability P_t for the economy as a whole:

$$P_t = \sum_{j=1}^{J} \sigma_j \Pi_{j,t} \tag{8}$$

$$\sigma_j = \frac{\sum_{j=1}^{J} w_i^j}{\sum_{i=1}^{N} w_i} \tag{9}$$

where σ_j is the weight assigned to sector j of the economy.[9] The crisis probability P_t is calculated as a weighted average of crisis probabilities associated to each sector of the economy $\Pi_{j,t}$. The higher P_t, the higher the probability to experience a currency crisis.

IV. Results

A. Parametric EWS

We begin estimating a fixed effects logit model where the dependent variable, or crisis incidence, Y_{it} defined in (3) is regressed on a set of macroeconomic indicators, which are

[9] We impose that the sum of the sectoral weights is equal to one.

believed to be relevant in anticipating currency crises in EMs. For the choice of the explanatory variables, we follow a general-to-specific approach to obtain a parsimonious specification of the model, where the explanatory variables have the desired sign and are significant in explaining crisis incidence. The explanatory variables are real GDP growth (ΔRGDP), the growth rate in the stock of foreign exchange reserves (ΔFXR), the ratio between the current account balance and nominal GDP (CAB/Y), the ratio between the stock of foreign exchange reserves (henceforth reserves) and short-term external debt (e.g. maturing within one year, FXR/STED), the ratio between M2 expressed in U.S. dollars and the stock of reserves (M2/FXR), and on a political risk variable which measures the degree of government instability (GOVT. INST). We consider three separate estimation periods, as we are interested to check how the coefficient estimates of the explanatory variables change if the global financial crisis of 2008-2009 is included or not in the estimation period. The three estimation periods are: January 1995-December 2006, January 1995-December 2007 and January 1995-December 2008.

Table 1: Parametric EWS: Fixed Effects Logit Model

	Jan. 95 - Dec. 06	Jan. 95 - Dec. 07	Jan. 95 - Dec. 08
	Dependent variable: Y_{it}		
ΔRGDP	-0.120	-0.061	-0.058
	(0.021)*	(0.018)*	(0.017)*
ΔFXR	-0.021	-0.040	-0.023
	(0.008)*	(0.007)*	(0.006)*
CAB/Y	-0.348	-0.267	-0.232
	(0.024)*	(0.019)*	(0.016)*
FXR/STED	-0.012	-0.008	-0.008
	(0.001)*	(0.001)*	(0.001)*
GOVT. INST.	0.112	0.119	0.125
	(0.038)*	(0.033)*	(0.029)*
M2/FXR	0.129	0.159	0.185
	(0.039)*	(0.031)*	(0.030)*
Observations	3113	3568	3880
Log-Likelihood	-889	-1232	-1449

$^{*}p < 0.01$

Table 1 reports the coefficient estimates obtained with the fixed effects logit model.[10] All the coefficient estimates are significant in explaining crisis incidence and have the expected

[10]Constant terms have been dropped from the panel regression, see Wooldridge (2002).

sign.[11]

In all the specifications, real GDP growth, the ratio between reserves and short term external debt, the growth rate in the stock of reserves and the current account balance are all significant and negatively related with crisis incidence. By contrast, a political risk explanatory variable measuring the degree of government instability is significant and positively related with crisis incidence.[12] Intuitively, doubts about government stability may create uncertainty about future macroeconomic policy, trigger portfolio outflows and currency depreciation.[13] The ratio between the domestic money stock expressed in U.S. dollars and the stock of reserves is also significant and positively related with crisis incidence. This result is in line with the work of Calvo and Mendoza (1996), who looked at the 1994 Mexican financial crisis and observed that in Mexico the domestic money stock expressed in U.S. dollars increased much faster than that of gross foreign exchange reserves during in the five years before the crisis. A persistently rising ratio between M2 and reserves indicates that a credit expansion is taking place, which is incompatible with a fixed exchange rate regime.[14]

In other (not reported) regressions, we replaced among the explanatory variables the ratio between M2 and reserves with private credit as a percentage of nominal GDP. Private credit as a percentage of nominal GDP, expressed in differences, is significant and positively associated with the crisis incidence and have the expected sign. By contrast, the level of private credit as a percentage of nominal GDP does not have the expected sign when the estimation sample is set between January 1995 and December 2006.

Other explanatory variables were not significant and are not presented in the table 1. Monthly changes in real effective exchange rates and a measure of real effective exchange rate misalignment were not significant.[15] Similarly, neither credit to the government as a percentage of nominal GDP (expressed in both levels and differences), nor the level of

[11]Real GDP growth and government instability lose significance after the beginning of the global financial crisis. Real GDP growth ceases to be significant when the time dimension of the sample period includes 2009, while government instability is no longer significant when the sample includes 2010. By contrast, all the remaining explanatory variables appear to be consistently significant when the time dimension of the panel is extended.

[12]The indicator of government instability is an assessment of both of the governments ability to carry out its declared program, and its ability to stay in office.

[13]This finding is in line with the notion that political instability may breed economic instability, see Gourinchas and Obstfeld (2011) and Acemoglu and others (2003).

[14]Under a fixed exchange rate regime, the money stock cannot increase indefinitely, otherwise it generates a persistent excess supply of domestic currency, which the central bank cannot offset as its stock of reserves is finite.

[15]As in Gourinchas and Obstfeld (2011), real effective exchange rate misalignment was measured as the log deviation from a time trend using a Hodrick-Prescott Filter.

reserves were significant. A measure of political risk assessing the presence of corruption in the political system was not found to be significant to explain crisis incidence. All in all, the coefficient estimates obtained with all specifications suggest that monetary expansions, which may reflect rapid increases in credit growth, are expected to increase crisis incidence, hence the likelihood of exchange rate depreciation. Summing up, the results obtained with the fixed effect logit regression appear to be in line with some of the empirical studies on currency crises. Frankel and Saravelos (2012), Gourinchas and Obstfeld (2011), and Llaudes and others (2010) find that reserves play an important role in reducing the likelihood of experiencing currency crises.

B. Non-parametric EWS

In this section, we calculate optimal thresholds and weights of each macroeconomic indicator that we use to construct the crisis probability with the non-parametric EWS. We group the indicators into three different groups: the domestic sector (which includes the real GDP growth and the measure of government instability), the external sector (which includes the growth rate of the stock of foreign exchange reserves, the ratio between the stock of foreign reserves and the stock of short -term external debt, the current account balance in percent of nominal GDP, and the monthly differences in the real effective exchange rate), and the financial sector (which includes the ratio between the money stock expressed in U.S. dollars and the stock of foreign reserves, credit to the private sector as a percentage of nominal GDP in levels and differences, and the level of credit to the government as a percentage of nominal GDP).

We are interested to check whether optimal thresholds and weights of each indicator change if the global financial crisis of 2008-2009 is included or not in the estimation period. We consider three different estimation periods: January 1995-December 2006, January 1995-December 2007 and January 1995-December 2008. For each indicator, tables 2-4 report optimal thresholds, weights, as well as type 1 and type 2 errors calculated in correspondence of the optimal threshold.

Tables 2-4 show that across periods, the current account balance as a percentage of nominal GDP and the ratio between the stock of foreign exchange reserves and short-term external debt are the two most reliable indicators in issuing crisis signals as they have the largest weights. The real GDP growth rate, the change in foreign exchange reserves, and the ratio between the domestic money stock expressed in U.S. dollars and foreign exchange reserves

Table 2: Non-parametric EWS: January 1995-December 2006

	Estimation period: January 1995-December 2006				
	Direction to be safe	Type 1 error	Type 2 error	Threshold	Weight
ΔRGDP	>	0.72	0.10	0.45	0.20
ΔFXR	>	0.65	0.16	-1.80	0.23
CAB/Y	>	0.28	0.45	-1.48	0.36
FXR/STED(in%)	>	0.59	0.17	90.74	0.32
GOVT. INST.	<	0.27	0.65	2.00	0.05
M2/FXR	<	0.58	0.30	3.43	0.14
Other indicators					
CPR/Y	<	0.00	0.86	16.77	0.15
ΔCPR/Y	<	0.88	0.05	0.26	0.07
ΔREER	<	0.31	0.56	0.06	0.14
ΔCPB/Y	<	0.35	0.56	-0.01	0.08

also contribute to the crisis probability, but carry lower weights. The lowest weight is assigned to government instability. The weights of all the indicators used (except those of the level of current account balance as a percentage of nominal GDP and the difference in credit to the government as a percentage of nominal GDP) decline when the estimation period includes the 2008-09 global financial crisis. By construction, the lower the weight of a given indicator, the higher its total misclassification error, the lower its contribution to calculate the crisis probability and its reliability in issuing crisis signals.[16] The results in tables 2-4 show that the reliability of the indicators in issuing crisis signals declines when the estimation period includes the global financial crisis of 2008-09. The declining reliability in issuing crisis signals may reflect the fact that the EWS presented in this paper are based mainly on 'traditional' macroeconomic indicators, and do not include those factors that are believed to have played a role in the development of the global financial crisis. For instance, neither of the EWS presented in this paper include measures of financial vulnerabilities,[17] investors' preferences,[18] cross-border financial linkages, and financial contagion.[19] In addition, the declining ability of the EMs macroeconomic indicators in issuing crisis signals may also reflect that fact that for a number of EMs, the global financial crisis of 2008-09 was an externally driven event.[20]

[16]See condition (6).
[17]See Berkmen and others (2012).
[18]See Milesi-Ferretti and Tille (2011).
[19]See Frank and Hesse (2009).
[20]See Llaudes and others (2010).

Table 3: Non-parametric EWS: January 1995 December 2007

	Estimation period: January 1995-December 2007				
	Direction to be safe	Type 1 error	Type 2 error	Threshold	Weight
ΔRGDP	>	0.61	0.29	0.45	0.15
ΔFXR	>	0.70	0.15	-1.93	0.17
CAB/Y	>	0.29	0.44	-1.48	0.35
FXR/STED(in%)	>	0.56	0.22	108.31	0.26
GOVT. INST.	<	0.42	0.59	2.50	0.05
M2/FXR	<	0.46	0.42	2.83	0.14
Other indicators					
CPR/Y	<	0.00	0.87	16.3	0.14
ΔCPR/Y	<	0.78	0.12	0.19	0.11
ΔREER	<	0.37	0.55	0.06	0.08
ΔCPB/Y	<	0.27	0.66	0.00	0.06

Tables 2-4 also report optimal threshold values for each indicator. When the global financial crisis is included in the in-sample period, the threshold of the ratio between foreign exchange reserves and short-term external debt is higher as it raises from 90 percent to 108 percent. Intuitively, a higher threshold for the ratio between foreign exchange reserves and short-terms external debt means that after the beginning of the global financial crisis, EMs needed more reserves relatively to their short-term external debt to be better insured against the risk of experiencing disruptive capital outflows.

Summing up, both the parametric and non-parametric EWS assign an important role to the external sector indicators. Government instability is significant and positively associated with crisis incidence only in the parametric EWS. From a policy perspective, the results imply that those EMs with good macroeconomic indicators and that had improved their policy fundamentals in the pre-crisis period, are likely to have suffered less from the impact of the global financial crisis.[21]

V. Comparing Performances of EWS

We now turn to assess which of the EWS used in this study has the highest ability in correctly predicting in-sample and out-of-sample crisis and tranquil periods. We proceed as

[21] See Llaudes and others (2010).

Table 4: Non-parametric EWS: January 1995-December 2008

	Estimation period: January 1995-December 2008				
	Direction to be safe	Type 1 error	Type 2 error	Threshold	Weight
ΔRGDP	>	0.78	0.10	0.59	0.13
ΔFXR	>	0.69	0.16	-1.80	0.17
CAB/Y	>	0.28	0.46	-1.36	0.36
FXR/STED(in%)	>	0.58	0.22	108.29	0.24
GOVT. INST.	<	0.71	0.26	5.00	0.03
M2/FXR	<	0.46	0.42	2.86	0.14
Other indicators					
CPR/Y	<	0.45	0.43	39.3	0.14
ΔCPR/Y	<	0.73	0.16	0.14	0.11
ΔREER	<	0.12	0.85	-0.01	0.04
ΔCPB/Y	<	0.21	0.74	-0.03	0.05

follows. First, we derive in-sample and out-of-sample crisis probabilities for the parametric and the non-parametric EWS. Second, we determine optimal cut-off values for the crisis probabilities in the same way we determined optimal thresholds for the individual indicators.[22] Then, in correspondence of the optimal cut-off values, we check how the parametric and non-parametric EWS perform in correctly predicting in-sample and out-of-sample crisis episodes and tranquil periods. We compare the performance of three different EWS:

1. **Parametric EWS (P)**: In this EWS, the crisis probability has been obtained by estimating a fixed effects logit model;

2. **Non-parametric 1 EWS (NP1)**: With this non-parametric approach the crisis probability has been calculated using the same macroeconomic indicators employed in the parametric EWS;

3. **Non-parametric 2 EWS (NP2)**: In this EWS, the indicators used in the Non-Parametric 1 EWS have been complemented by the change in the real effective exchange rate, and measures of credit to the government and to the private sector.

At this stage, to assess the performance of the non-parametric EWS, we introduce an important assumption about the policymaker's policy preferences. Specifically, we will

[22]See section III.B.

initially assume that the policymaker assigns the same weight to type 1 and type 2 errors. Put differently, the policymaker dislikes in equal way the risk of missing a crisis and that of issuing a false alarm. The total misclassification error is expressed as follows:

$$z = \left(\frac{1}{2}\right) \; type \; 1 \; error + \left(\frac{1}{2}\right) \; type \; 2 \; error \tag{10}$$

where

$$type \; 1 \; error = \frac{total \; missed \; crises}{total \; crises}$$

$$type \; 2 \; error = \frac{total \; false \; alarms}{total \; non-crises}$$

In a second stage, we assume that the policymaker becomes more cautious, in the sense that she dislikes more missing a crisis episodes than issuing a false alarm. This can be motivated by the consideration that the policymaker thinks that missing a crisis can potentially be much costlier than issuing a false alarm in terms of foregone output. Therefore, compared to (10), the total misclassification error is amended as follows:

$$z = \left(\frac{2}{3}\right) \; type \; 1 \; error + \left(\frac{1}{3}\right) \; type \; 2 \; error \tag{11}$$

We make these assumptions about the policymaker's policy preferences because we are interested to check how the non-parametric EWS performance changes when the policymaker's preferences change as well.

A. The Policymaker Assigns Equal Weights To Type 1 and Type 2 Errors

We derive optimal cut-off values for the crisis probabilities of the parametric and non-parametric EWS. For each crisis probability, crisis period observations have been collected in a subsample and separated from tranquil period observations. For each subsample (e.g. crisis and tranquil periods), cumulative density functions, as well as type 1 and type 2 errors have been calculated. An optimal cut-off value for the crisis probability has been chosen such that, in its correspondence, the sum between type 1 and type 2 errors is minimized. Put differently, there is no other cut-off value that separates better the crisis period subsample from the tranquil period subsample than the optimal cut-off value. The policymaker assigns the same weight to the risk of missing crises and to that of issuing false alarms.

Table 5: The Policymaker Assigns Equal Weights To Type 1 and Type 2 Errors

	Jan 95 - Dec 06			Jan 95 - Dec 07			Jan 95 - Dec 08		
In-sample	P	NP1	NP2	P	NP1	NP2	P	NP1	NP2
Probability critical threshold	**0.25**	**0.26**	**0.35**	**0.39**	**0.26**	**0.31**	**0.44**	**0.27**	**0.27**
% of crises correctly called	59.1	52.0	46.0	56.5	48.9	48.5	53.6	49.9	60.0
% of tranquil periods correctly called	65.6	79.4	81.0	67.1	81.3	79.9	70.1	79.6	72.5
Probability of crisis given alarm	45.0	54.6	53.6	47.0	57.4	55.5	48.3	56.1	53.4
Probability of crisis given no alarm	22.9	22.4	24.1	25.1	24.5	25.0	25.7	24.8	22.4
Total misclassification error	75.3	68.3	73.0	76.4	69.8	71.6	76.3	70.6	67.5
	Jan 07 - Dec 11			Jan 08 - Dec 11			Jan 09 - Dec 11		
Out-of-sample	P	NP1	NP2	P	NP1	NP2	P	NP1	NP2
Probability critical threshold	**0.25**	**0.26**	**0.35**	**0.39**	**0.26**	**0.31**	**0.44**	**0.27**	**0.27**
% of crises correctly called	61.7	44.5	57.3	44.1	42.6	60.8	95.2	41.3	93.7
% of tranquil periods correctly called	74.4	71.5	69.6	85.0	71.2	65.4	72.5	72.0	51.7
Probability of crisis given alarm	37.7	28.1	32.1	34.5	21.0	23.9	18.8	8.9	11.5
Probability of crisis given no alarm	11.4	16.3	13.3	10.5	12.6	9.7	0.4	5.2	0.8
Total misclassification error	63.9	84.0	73.1	70.9	86.1	73.9	32.3	86.8	54.6

In table 5 we report the in-sample and out-of-sample performances of the parametric and non-parametric EWS when the policymaker assigns the same weight to the risk of missing crises and to that of issuing false alarms. For each EWS we report:

- The percentage of crisis episodes correctly called, calculated as the ratio between the number of correctly predicted crisis episodes and the total number of crisis episodes observed;
- The percentage of tranquil periods correctly called, calculated as the ratio between correctly predicted non-crisis episodes and the total number of non-crisis episodes observed;
- The probability of crisis given an alarm issued;
- The probability of crisis given no alarm issued;
- The total misclassification error, calculated as the sum of the ratio between the number

of missed crises over the number of observed crisis episodes and the ratio between the number of false alarms over the number of observed tranquil periods;

The main point is that not always in-sample performances are superior to out-of-sample performances. The in-sample total misclassification error of the parametric EWS ranges between 75.3% and 76.4%, while the out-of-sample error ranges between 32.3% and 70.9%. The out-of-sample error of the parametric EWS declines because the percentages of correctly called crisis episodes and tranquil periods rise compared to the in-sample period. In this context, it is particularly striking to observe that in two cases out of three (P and NP2), when the out-of-sample period is restricted to the period between January 2009 and December 2011, the ability to correctly call out-of-sample crisis episodes is very high (P and NP2). This is because the number of missed out-of-sample crisis is very low.[23]

The parametric EWS is more reliable in correctly predicting out-of-sample crisis episodes than the non-parametric EWS. The probability of an out-of-sample crisis episode when the parametric EWS issues an alarm is higher than the probability of an out-of-sample crisis when the non-parametric EWS issue an alarm. The parametric EWS tends to have lower probabilities than the non-parametric EWS of missing crisis episodes when the EWS fails to issue an alarm.

Overall, when the policymaker assigns the same weight to the risk of missing crises and to that of issuing false alarms, the results show that the parametric EWS achieves superior out-of-sample results compared to the non-parametric EWS, as the total misclassification error of the former is lower than that of the latter. In addition, the striking increase in the percentages of correctly called out-of-sample crisis episodes by two of the three EWS considered during the period January 2009 - December 2011 (95.2% and 93.7% respectively) shows that EWS mainly relying on traditional macroeconomic indicators perform quite well. Indeed, following the most turbulent year of the global financial crisis, 2008, the two EWS improve markedly their out-of-sample performance, since during the periods January 2007-December 2011 and January 2008-December 2011 the percentages of correctly called out-of-sample crisis range between 44% and 61%. One possible interpretation of this result is that following 2008, international investors may have been assigning more importance to macroeconomic indicators when assessing their exposure toward EMs assets.

[23]There are only three cases of out-of-sample missed crises between January 2009 and December 2011 across the EMs included in the panel.

Table 6: A More Cautious Policymaker

	Jan 95 - Dec 06			Jan 95 - Dec 07			Jan 95 - Dec 08		
In-sample	P	NP1	NP2	P	NP1	NP2	P	NP1	NP2
Probability critical threshold	**0.03**	**0.03**	**0.21**	**0.11**	**0.21**	**0.17**	**0.12**	**0.19**	**0.22**
% of crises correctly called	87.4	82.3	79.0	86.8	74.3	78.9	87.7	77.3	74.5
% of tranquil periods correctly called	36.2	39.8	46.0	37.2	54.7	45.7	34.4	52.4	53.6
Probability of crisis given alarm	39.5	39.4	41.1	41.7	45.9	42.9	41.2	46.0	45.7
Probability of crisis given no alarm	14.2	17.5	17.9	15.5	19.5	19.3	15.8	18.5	20.0
Total misclassification error	76.4	77.9	75.0	76.0	70.9	75.4	77.9	70.3	72.0
	Jan 07 - Dec 11			Jan 08 - Dec 11			Jan 09 - Dec 11		
Out-of-sample	P	NP1	NP2	P	NP1	NP2	P	NP1	NP2
Probability critical threshold	**0.03**	**0.03**	**0.21**	**0.11**	**0.21**	**0.17**	**0.12**	**0.19**	**0.22**
% of crises correctly called	85.2	76.9	76.6	76.5	76.0	79.9	96.8	96.8	96.8
% of tranquil periods correctly called	30.8	37.7	44.9	52.9	48.6	40.4	26.1	46.1	42.6
Probability of crisis given alarm	23.6	23.6	25.9	22.5	20.9	19.3	8.0	10.7	10.1
Probability of crisis given no alarm	10.8	13.4	11.6	7.4	8.1	8.2	0.8	0.5	0.5
Total misclassification error	84.1	85.5	78.5	70.6	75.4	79.7	77.0	57.0	60.5

B. A More Cautious Policymaker

We now turn to assume that the policymaker assigns a relatively higher weight to the risk of missing crisis episodes than to the risk of issuing false alarms. This will induce the policymaker to be more cautious and select a lower critical value for the crisis probability compared to the previous case when she assigned the same weight to type 1 and type 2 errors. The main point is that the performances of the parametric and non-parametric EWS do not improve if the policymaker becomes more cautious. Table 6 shows that the total misclassification error tends to increase when the policymaker assigns a larger weight to the risk of missing a crisis than to that of issuing a false alarm. This implies that if the policymaker becomes more cautious, hence more averse to missing crisis episodes, the benefit of correctly calling more in-sample and out-of-sample crisis episodes tends to be more than offset by the cost of issuing more in-sample and out-of-sample false alarms.

From a macroeconomic policy perspective, the policymaker faces then the standard trade-off when using EWS. On the one hand, greater aversion to missing crisis episodes allows the policymaker to correctly predict more crises. But, on the other hand, more cautiousness implies that the policymaker is likely to issue more false alarms compared to a situation of more balanced policy preferences. The higher the number of false alarms, the higher the risk of implementing corrective macroeconomic policies when a crisis does not happen. More generally, the benefit of correctly calling more crisis episodes needs to be weighed against the risk of issuing many false alarms and the costs of implementing corrective macroeconomic policies prematurely.

VI. Conclusions

In this study we compared the performance of parametric and non-parametric EWS in correctly predicting in-sample and out-of sample currency crisis in EMs.

We find that both the parametric and non-parametric EWS assign an important role to 'traditional' macroeconomic indicators, such as the real GDP growth rate, the current account balance as a percentage of nominal GDP, the monthly growth rate in foreign exchange reserves, the ratio between the money stock and foreign exchange reserves, and the ratio between foreign exchange reserves and short-term external debt. In the parametric EWS, the measure of government instability is significant and positively associated with crisis incidence, while in the non-parametric EWS it turns out to be a much less reliable indicator than the macroeconomic indicators. From a macroeconomic policy perspective, the results obtained with the parametric and non-parametric EWS imply that those emerging market economies with good macroeconomic indicators and that had improved their policy fundamentals in the pre-crisis period, are likely to have suffered less from the impact of the global financial crisis.[24]

In terms of performance, we find that when the policymaker equally dislikes missing crisis episodes and issuing false alarms, the parametric EWS achieves superior out-of-sample results compared to the non-parametric EWS, as the total misclassification error of the former is lower than that of the latter. We also find that the percentages of correctly called out-of-sample crisis episodes by two of the three EWS during the period January 2009-December 2011 increase substantially compared to those out-of-sample periods which included 2007 and/or 2008. One possible interpretation of this result is that after 2008, the most turbulent year of the global financial crisis, international investors may have been paying more attention to macroeconomic indicators when assessing their exposure toward EMs assets.

The performance of the parametric and non-parametric EWS does not improve if the policymaker becomes more averse to the risk of missing crisis episodes, as the total

[24]See Llaudes and others (2010).

misclassification error tends to increase. While a more cautious policymaker correctly calls more crisis episodes compared to a policymaker with more balanced policy preferences, the former issues more false alarms compared to the latter. This implies that the benefit of correctly calling more in-sample and out-of-sample crisis episodes is more than offset by the cost of issuing more in-sample and out-of-sample false alarms. From a macroeconomic policy perspective, the policymaker faces the standard trade-off when using EWS. On the one hand, a greater degree of caution allows the policymaker to correctly predict more crises. But, on the other hand, more prudence leads the policymaker to issue more false alarms. The higher the number of false alarms, the higher the risk of implementing corrective macroeconomic policies when a crisis does not happen. More generally, the benefit of correctly calling more crisis episodes needs to be weighed against the risk of issuing many false alarms and the costs of implementing corrective macroeconomic policies prematurely.

The analysis in this study can be extended in several ways. First, the EWS used in this study rely mainly on the information conveyed by standard macroeconomic indicators. It would be interesting to assess if and how in-sample and out-of-sample performances change if indicators quantifying contagion, spillover effects or cross-border financial linkages are included in the EWS. Second, it would be interesting to include in the panel also those emerging and developing economies that never experienced a currency crisis before, assuming that sufficient data is available, to see how the estimates and EWS performance change. Finally, it would be interesting to check whether there are more elaborated measures of real effective exchange rate misalignment that could be significant in explaining crisis incidence in the parametric EWS.

Appendix

A1. Country List

Argentina, Brazil, Bulgaria Chile, Colombia, Croatia, Egypt, Hungary, India, Indonesia, Kazakhstan, Korea (Republic of), Lebanon, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Romania, Russia, South Africa, Taiwan, Thailand, Turkey, Ukraine, Uruguay and Vietnam.

A2. Description of the variables

1. Real GDP growth ΔY: Annual percentage change in real GDP. Annual data have been interpolated in order to have monthly time series for real GDP growth. Source: World Economic Outlook Database, International Monetary Fund.

2. Change in the real effective exchange rate Δ REER: Annual percentage change in the real effective exchange rate, calculated in each month. Source: International Financial Statistics (IFS), International Monetary Fund.

3. Change in the stock of foreign exchange reserves Δ FXR: Monthly percentage changes in foreign exchange reserves less gold. Source: International Financial Statistics (IFS), International Monetary Fund.

4. Ratio between the money stock M2 expressed in U.S. dollars and foreign exchange reserves, M2/FXR. An unstable ratio may indicate a lending boom, which can be consistent with the expectation of currency depreciation, in case the government intervenes to recapitalize those banks which have accumulated non-performing loans, thereby increasing the money stock. Sources: International Financial Statistics and Haver Analytics.

5. Current account balance as a percentage of GDP, CAB/Y. Ratio between the current account balance and nominal GDP. Annual data have been interpolated in order to have monthly time series for the current account balance expressed as a percentage of nominal GDP. Source: World Economic Outlook Database, International Monetary Fund.

6. Ratio between foreign exchange reserves and short term external debt, FXR/STED: This is calculated as the ratio between the stocks of foreign exchange reserves and short-term external debt (i.e. maturing within one year). Both numerator and

denominator are expressed in U.S. Dollars. It is a reserve adequacy ratio which is often used in early warning exercises. Source: Joint External Debt Hub (jedh.org).

7. Ratio between private credit and nominal GDP, CPR/Y. Monthly data, available for most emerging economies only from January 2001 onwards.

8. Monthly growth rate of the ratio between private credit and nominal GDP, Δ CPR/Y.

9. Government instability, GOVT. INST.: Government instability is one of the twelve components of the political risk rating of International Country Risk Guide Database (Political Risk Services). The government instability index can assume values between 1 and 6. The index has been transformed so that the higher the score, the higher the degree of political instability. Source: International Country Risk Guide (ICRG) Database.

References

Abiad, Abdul, 2003, ”Early Warning Systems: A Survey and a Regime-Switching Approach”, *IMF Working Paper*, WP/03/32, (Washington DC: International Monetary Fund).

Acemoglu, Daron, Simon Johnson, James Robinson and Yunyong Thaichareon, 2003, ”Institutional Causes, Macroeconomic Symptoms: Volatility, Crises and Growth”, *Journal of Monetary Economics*, Vol. 50 (1), pp. 49-123.

Beckmann, Daniela, Lukas Menkhoff, and Katja Sawischlewski, 2006, ”Robust Lessons About Practical Early Warning Systems”, *Journal of Policy Modeling*, Vol. 28, pp. 163-193.

Berg, Andrew, and Catherine Pattillo, 1999, ”Predicting Currency Crises: The Indicators Approach and an Alternative”, *Journal of International Money and Finance*, Vol. 18, pp. 561-586.

Berkmen, S. Pelin, Gaston Gelos, Robert Rennhack, and James Walsh, 2012, ”The global financial crisis: Explaining cross-country differences in the output impact”, *Journal of International Money and Finance*, Vol. 31, pp. 42-59.

Blanchard, Olivier, Mitali Das, and Hamid Faruqee, 2010, ”The Initial Impact of the Crisis on Emerging Market Countries”, *Brooking Papers on Economic Activity*, Spring 2010, pp. 263-323.

Bussiere, Matthieu, and Marcel Fratszcher, 2006, ”Towards a New Early Warning System of Financial Crises”, *Journal of International Money and Finance*, Vol. 25, pp. 953-973.

Calvo, Guillermo A., and Enrique G. Mendoza, 1996, ”Mexico’s balance-of-payments crisis: a chronicle of a death foretold” *Journal of International Economics*, Vol. 41, pp. 235-264.

Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christopher Hurlin, 2012, ”How to Evaluate an Early-Warning System: Toward a Unified Statistical Framework for Assessing Financial Crises Forecasting Methods” *IMF Economic Review*, Vol. 60, No.1, (Washington DC: International Monetary Fund).

Cerra, Valerie, and Sweta C. Saxena, 2008, ”Growth Dynamics: The Myth of Economic Recovery” *American Economic Review*, Vol. 98, No.1 (March 2008), pp. 439-457.

Dabla-Norris, Era, and Yasemin Bal Gündüz, 2012, ”Exogenous Shocks and Growth Crises in Low-Income Countries: A Vulnerability Index”, International Monetary Fund Working Paper No. WP/12/264, (Washington DC: International Monetary Fund).

Eichengreen, Barry, Andrew K. Rose, and Charles Wyplosz, 1995, ”Exchange Market Mayhem”, *Economic Policy*, Vol. 10, No. 21, pp. 249-312.

Frank, Nathaniel, and Heiko Hesse, 2009, ”Financial Spillovers to Emerging Markets during the Global Financial Crisis”, International Monetary Fund Working Paper No. WP/09/104 (Washington DC: International Monetary Fund).

Frankel, Jeffrey, and George Saravelos, 2012, ”Can Leading Indicators Assess Country Vulnerability? Evidence From the 2008-09 Global Financial Crisis”, *Journal of International Economics*, Vol. 87, pp. 216-231.

Gourinchas, Pierre-Olivier, and Maurice Obstfeld, 2011, ”Stories of The Twentieth Century For The Twenty-first”, NBER Working Paper No. 17252, (Cambridge, Massachusetts: National Bureau of Economic Research).

International Monetary Fund, 2002, ”Global Financial Stability Report”, March 2002, Chapter 4, International Monetary Fund (Washington DC: International Monetary Fund).

——, 2013 (forthcoming), ”The IMF-FSB Early Warning Exercise: Design and Methodological Toolkit”, International Monetary Fund Occasional Paper No. 274, (Washington DC: International Monetary Fund).

Kaminsky, Graciela L., 1998, ”Currency and Banking Crises: The Early Warning of Distress”, International Finance Discussion Paper No. 629, (Washington DC: Board of Governors of the Federal Reserve System).

Kaminsky, Graciela L., Saul Lizondo and Carmen M. Reinhart, 1998, ”Leading Indicators for Currency Crisis”, *IMF Staff Papers*, Palgrave Macmillan Journals, 45(1).

Kaminsky, Graciela L., and Carmen M. Reinhart, 1999, ”The Twin Crises: The Causes of Banking and Balance-of-Payments Problems”, *American Economic Review*, Vol. 89, No. 3, pp. 473-500.

Llaudes, Ricardo, Ferhan Salman and Mali Chivakul, ”The Impact of the Great Recession on Emerging Markets”, International Monetary Fund Working Paper No. WP/10/237, (Washington DC: International Monetary Fund).

Milesi-Ferretti, Gian Maria, and Cédric Tille, 2011, "The great retrenchment: international capital flows during the global financial crisis", *Economic Policy*, Vol. 26, No. 66, pp. 289-346.

Rose, Andrew, and Mark M. Spiegel, 2012, "Cross-country Causes and Consequences of the 2008 Crisis: Early Warning", *Japan and the World Economy*, Vol. 24, pp. 1-16.

Wooldridge, Jeffrey M., 2002, Econometric Analysis of Cross Section and Panel Data, *MIT Press*, (Cambridge: Massachusetts Institute of Technology Press).