Terra Economicus, 2022, 20(4): 115–128
DOI: 10.18522/2073-6606-2022-20-4-115-128

Leading indicators of currency crises: Discriminant function analysis vs Early warning signal approach

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Citation: Kahraman S., Sariyer G. (2022). Leading indicators of currency crises: Discriminant function analysis vs Early warning signal approach. *Terra Economicus* **20**(4), 115–128. DOI: 10.18522/2073-6606-2022-20-4-115-128

Money markets play a key role in macroeconomic stability. This study aims to extend discriminant function analysis and apply early warning models to detect the signalling indicators of the currency crises in developing countries for the period between 1987 and 2007. The obtained model based on the data on India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Russia, Turkey and Thailand then tested in another set of six developing countries including Argentina, Brazil, Chile, Colombia, Uruguay and Venezuela. The theoretical premise of the paper is based on the three-generation currency crisis models. The empirical findings indicate that current account balance / reserves, M2 growth (annual %), domestic credit provided by banking sector (%of GDP), bank liquid reserves to bank assets ratio (%), and GDP annual growth are the leading indicators of currency crises. The model provided by DFA has around 60% accuracy in foreseeing the status of crisis in the test data set. The results suggest that discriminant function analysis would be a useful tool to predict the "signal".

Keywords: *currency crisis; discriminant function analysis; currency crisis index; emerging market economies; early warning signal approach*

JEL codes: *G01, C49, E47, F41*

Опережающие показатели валютного кризиса: дискриминантный анализ и сигналы раннего предупреждения

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Цитирование: Kahraman S., Sariyer G. (2022). Leading indicators of currency crises: Discriminant function analysis vs Early warning signal approach. *Terra Economicus* **20**(4), 115–128. DOI: 10.18522/2073-6606-2022-20-4-115-128

Денежные рынки играют ключевую роль в обеспечении макроэкономической стабильности. Данное исследование направлено на расширение дискриминантного анализа и применение моделей, предназначенных для выявления на ранних стадиях признаков, сигнализирующих о валютных кризисах в развивающихся странах за период с 1987 по 2007 гг. Полученная модель основана на данных по нескольким странам, включая Индию, Индонезию, Южную Корею, Малайзию, Мексику, Филиппины, Россию, Турцию и Таиланд. Затем модель была протестирована на другой группе из шести развивающихся стран: Аргентина, Бразилия, Чили, Колумбия, Уругвай и Венесуэла. В теоретическом плане мы опираемся на модели валютных кризисов, имевших место на протяжении трех поколений. Эмпирические данные показывают, что основными показателями валютных кризисов выступают соотношение между сальдо счета текущих операций и резервами, годовой рост М2 (%), внутренний кредит, предоставленный банковским сектором (отнесённый к ВВП), отношение банковских ликвидных резервов к банковским активам (%) и годовой рост ВВП. Точность полученной на основе дискриминантного анализа модели для прогнозирования кризисного состояния составила около 60%. Результаты показывают, что дискриминантный анализ может быть полезным инструментом для выявления предвестников валютного кризиса на ранних этапах.

Ключевые слова: *валютный кризис; дискриминантный анализ; показатели валютного кризиса; страны с формирующейся рыночной экономикой; сигнал раннего предупреждения*

1. Introduction

A currency crisis may be defined as a situation in which a sudden speculative attack on domestic currency results in a sharp depreciation of the currency, international reserve loses or both. After the financial liberalization period of 1980s, many developing countries have faced currency crises due to the similar reasons. Economists mainly focus on building models to find out the sources of these crises instead of effects and the policy suggestions. Economists at the IMF have implemented several models to predict currency crises and balance of payment crises. Early warning signal approach developed by Kaminsky et al. (henceforth KLR) in 1998 is a model to predict the leading indicators for potential crisis. In conducting the discriminant function analysis, our study aims at contributing to the literature in two ways. First, this study is the one which performs the discriminant function analysis to understand crisis signals. Second, and the most important one, the argument of our study is that the signalling indicators of one country can be used to explain the currency crises in another country. This approach is stated by Kaminsky (2006) as "one fits all", which also motivates us to conduct the study. Moreover, the third-generation models of currency crises explain the theoretical ground of this argument as well as this research.

This paper summarizes the main theoretical explanations for currency crises, and proposes a discriminant function analysis. Section two presents traditional approach to study currency crises. The third section reviews the empirical literature on early warning models used to determine leading indicators of potential currency crises. Section four explains data and research methodology. Section five presents our findings. Section six discusses the results. Finally, the last section concludes the paper.

2. The anatomy of currency crises: Traditional approach

In the history of economic thought there is no theoretical consensus regarding to sources of currency crises. However, theoretical models mainly consider the sources of crises. As seen in Table 1 the traditional approach emphasizes the role of weak macroeconomic fundamentals and expansionary economic policies.

Table 1

Leading Indicators of Currency Crises Models

Currency Crisis Models	Leading Indicators
First generation models	fiscal deficit/GDP
	excess real M1 balances
Second generation models	real exchange rate
	domestic real interest rate
	exports
	imports
	terms of trade
	output
Third generation models	M2 multiplier
	M2/foreign exchange reserves
	stock Prices
	dometic credit/GDP
	bank deposits
	banking crisis

Source: Kamisky, 2006: 509.

Krugman (1979) proposed the theoretical model of balance of payment crises known as first generation models based on the study of Salant and Dale (1978). First generation model shows that under a fixed exchange rate regime, expansionary monetary policy in excess money demand may lead a sudden loss of international reserves. When the economic agents understand that the monetary authorities are not able to maintain the exchange rate as a fixed, this process ends with a speculative attack on domestic currency. These models were characterised by a rapid domestic credit expansion in an excess money demand and well accounted the currency crises in Mexico and Latin America between the years 1973–1982 (Krugman, 1979).

The second-generation models proposed by Obstfeld (1986) have highlighted the role of pessimist expectations of economic agents. Moreover, without any macroeconomic weakness, economy may generate self-fulfilling balance of payment problems. Following the Asian Crises in 1997, the third generation models also known as contagion models proposed by Obstfeld (1996) were used to indicate the spread effect of currency crises and the moral hazard problems in financial markets. In contrast to previous episodes, these new models explain how crisis in one country spread to other countries mainly through the trade linkages and financial linkages. Thus, forecasting crises and contagion channels may be extremely difficult.

3. Literature review

Monetary economists mainly focus on the causes of currency crises by using econometric methods. Table 2 provides a summary of selected empirical studies on early warning signal approach. There are also paper series like those of Berg and Pattillo (1999a; b) which evaluate the performance of early warning system in the analysis of IMF. Authors assess the predictive power of KLR model for the 1997 Asian Crisis by comparing two other early warning models, probit model developed by Frankel and Rose (1996), and cross-country regression model elaborated by Sachs et al. (1996). Authors suggest that among the KLR models this model provides better forecast. In the same context, Berg et al. (2005) compare KLR models with non-model-based indicators, and point out that the KLR model decisively outperform. Moreover, since the world economies have faced COVID-19 pandemic, recent studies also examine the role of health crises. Reinhart's (2022) paper is such a study which indicates that the COVID-19 pandemic with weak macroeconomic fundamentals has signalled financial or debt crises.

Table 2

Early warning signal approach: A brief literature review

References	Country and crisis coverage	Indicators	Estimation results / Comments
Eichengreen et al. (1995)	20 countries (78 currency crises), 1959–1993 quarterly data	25 indicators from five broad categories: – financial sector, – real sector, – external sector, – public finance, – political variables	exchange rate interventions are the effective tool but there is no clear signalling indicator
Otker and Pazarbasıoglu (1996)	Mexico Crises (exchange rate interventions), 1982–1994, monthly data	– real exchange rate, – international reserves – inflation – output growth – US interest rates, – Central Bank credits – foreign currency debt – financial reform – fiscal deficit, – CAB	– international reserve loses, – inflation differentials, – share of short-term foreign currency debt, – appreciation of real exchange rate, – fiscal policies and monetary policies have linked to the exchange rate regime changes and speculative attacks
Flood and Marion (1997)	17 Latin American countries (80 peg episodes), 1957–1990, monthly data	– drift in real exchange rate, – variance of the real exchange rate	– stochastic components of the real exchange rate are leading signals for timing and size of devaluation
Kaminsky et al. (1998)	evaluate the empirical evidence to determine the best performer signal indicators	105 indicators from six categories: – financial sector, – real sector, – external sector, – public finance, – political variables, – institutional and structural variables	– exports, – deviations of the real exchange rate from trend, – the ratio of broad money to gross international reserves, – output and – equity prices

The end of the table 2

References	Country and crisis coverage	Indicators	Estimation results / Comments
Kaminsky and Reinhart (1999)	5 industrialised countries and 15 developing countries (76 currency crises, 26 banking crises), 1970–1994 monthly data	– real exchange rate, – banking crises, – stock prices, – exports, – M2/reserves, – output, – excess M1 balances, – reserves, – M2 multiplier, – domestic credit/nominal GDP, – terms of trade, – real interest rates, – interest rate differentials, – bank deposits, – imports	– about 80 percent of indicators were sending signal, – there is a strong correlation between banking crises and currency crises
Reinhart et al. (2000)	25 emerging economies (29 banking and 87 currency crises), 1970–1997	– 25 indicators from 5 broad categories: – financial sector, – real sector, – external sector, – public finance, – political variables	– real exchange rate appreciation, – equity prices, – export ratio, – broad money to reserve ratio, – recession, and – current account deficit relative to both GDP and investment
Edison (2003)	20 countries, 1970–1995	indicators used in KLR: – current account indicators, – capital account indicators, – real sector indicators, – financial indicators	currency crises have similar fragility characteristics and common leading indicators
Kaminsky (2006)	20 countries (96 currency crises), 1970–2002	18 macroeconomic indicators and financial indicators (subsequent version of Kaminsky and Reinhart 1999)	different currency crises generation models, empirical literature supports the "one fits all" approach
Reinhart and Rogoff (2011)	70 countries in Africa, Asia, Europe, Latin America, North America, and Oceania, 1865–2009	public debt/GDP, external debt as a % of GDP	private debt, public borrowing and banking crises may provoke debt crisis
Sevim et al. (2014)	Turkey, 1992–2011	Financial Pressure Index (FPI) as the dependent variable which composed of the % change in USD exchange rates, gross foreign exchange reserves and O/N interest rates and 32 macroeconomic indicators	– deviation in the foreign exchange rate and – decrease in international reserves. There is no crisis expectation for a year 2012
Mulder et al. (2016)	19 emerging market economies, 1991–2001	– debt structure, – leverage, – liquidity, and – profitability	banks' balance sheets
Kose et al. (2021)	10 emerging market and developing economies, aftermath of crises	– orthodox indicators: enhancing growth, fiscal consolidation, privatization, and wealth taxation, and – heterodox indicators: inflation, financial repression, debt default and restructuring	economic, social, and political costs are needed to forecast debt distress

4. Data and research methodology

In this paper, we employ discriminant function analysis to find out the causes of currency crises in selected countries. Our data set consist of annually observations for 16 developing countries over the period 1987–2007. These countries have experienced at least one currency crisis, and also have been considered within KLR model. Our sample involves nine countries data set including India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Russia, Turkey and Thailand. Another set of six countries including Argentina, Brazil, Chile, Colombia, Uruguay and Venezuela, is used to test the accuracy of the proposed model in crisis detection. The selection criteria of training data set are based on the major crises' experiences such as 1994 Mexico Crisis, 1997 Asian Crisis, 1998 Russian Crisis, and 1994, 2001 Turkey crises. These crises have spread to the rest of the world, mainly to test data country group. The dependent or criterion variable of the analysis is the crisis index. The explanatory variables used in the analysis can be group into the following indicator categories: current account, capital account, financial account, fiscal account, and real sector indicators. The data set consist of real interest rate (%), GDP annual growth (%), current account balance/reserves, export (% growth)/ import (% growth), portfolio investment/foreign direct investment (FDI), M2 growth (annual %), domestic credit provided by banking sector (%of GDP), bank liquid reserves to bank assets ratio (%), and cash surplus/deficit (% of GDP). The data source is International Financial Statistics – IMF Data.

4.1. Early Warning Signal Approach

While a large body of literature emphasizes the causes of currency crises, early warning signal approach focuses on both timing and leading indicators of currency crises. The most well-known early warning models are the probit/logit model (FR model – Frankel and Rose), the cross-sectional regression model (STV model – Sachs, Tornell and Velasco), and the signal approach or (KLR model – Kaminsky, Lizondo and Reinhart). Early warning signal approach as a non-parametric methodology is developed by Kaminsky, Lizondo and Reinhart (1998) and Kaminsky and Reinhart (1999). The lead position in implementation of this model is taken by IMF. In this approach, several macroeconomic indicators are monitored to detect the leading indicators within non-crisis period. When an indicator exceeds a threshold, that is an unusual behaviour of variables, treated as a "signal" for a potential currency crisis within next 24 months. On the other hand, methodology has some limitations such as the lack of ranking of the indicators according to their ability for forecasting. In addition, KLR model is based on the macroeconomic variables and monthly data. This limits the ability of the model to predict the potential currency crises. Although, discriminant function analysis is used in finance context to make discriminations between the categories of studied criterion variable (i.e. Kim, 2018; Othman and Asutay, 2018). This method is rarely applied in analyzing the crisis signals of countries.

4.2. Discriminant Function Analysis (DFA)

In the context of group intervals and racial similarity coefficients, DFA goes back to the 1930s and statistician K.Pearson and others. This statistical technique is developed by Fischer (1936) in order to solve linear problems based on the methodology used in multivariate linear regression and matrix algebra. DFA builds explanatory and predictive models for grouping the sample. It is used for categorizing the sample elements based on the levels (values) of a nominal scaled dependent variable having two or more categories, where the independent variables are metric (interval or ratio scaled). Thus, for data sets having nominal dependent variables and metric independent variables, DFA predicts the change in the dependent variable, or the group membership, based on the independent variables, or the model predictors. In DFA, model predictors form new variables with a *discriminant score* where this score is calculated for each elements of the sample. This new variable forming discriminant scores is labelled as *discriminant function* and is calculated in a way that the sample elements are categorized or grouped into levels of the dependent variable. This function combines the standardized independent variables linearly to have the maximum variation between groups (different levels of the dependent variable) and minimum variation within groups.

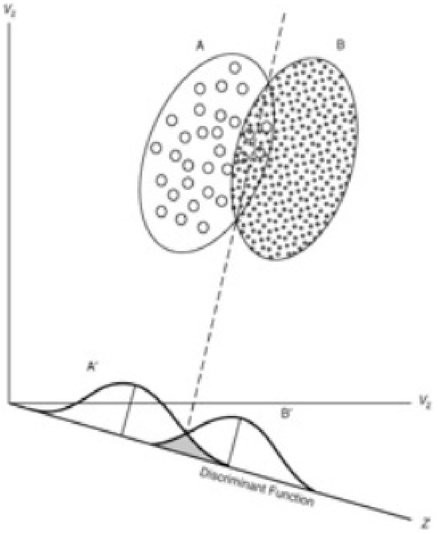

Figure 1. DFA with binary dependent variable

Source: Authors

Mathematically, assume $X_1, X_2, \ldots, X_n$ are the independent variables and Y is a nominal dependent variable. DFA aims to form linear functions with following structures:

$$D_i = a + b_1 X_1 + b_2 X_2 + \ldots + b_n X_n,$$

where b_j s are the weights associated with the model predictors and D_i is the predicted discriminant score of the dependent variable for the i^{th} element of the sample. When the dependent variable is binary (having two levels) as seen in Figure 1, DFA aims to assign each sample element to one of these two groups based on their calculated discriminant scores, namely D_is. The cut-off score which is found as the one resulting in the fewest classification error is calculated as the weighted mean scores of the two groups. Calculated discriminant scores of observations are then compared with cut-off score of the algorithm to classify the observation into one of these two groups appropriately. The efficiency of DFA in creating significant differences between groups is analysed by using Wilks' Lambda Test whose significance level is based on chi-square test. Wilks' Lambda varies between 0 and 1 and shows the variance of categorical dependent variable that is not explained by the discriminant function, thus lower values are desired.

5. Empirical Process and Findings

5.1. Empirical Process

Panel data set of this study includes 315 yearly observations in total for fifteen countries each having 21 years data. For each of these observations, crisis index values are calculated and grouped into two as: "Crisis index positive" and "Crisis index non-positive". Thus, years with zero crisis index value are accounted for the second group. In addition to afore-mentioned nine independent variables, year is used as another model predictor taking values between 1 and 21 where 1 represents year 1987 and 21 represents year 2007. Thus, in this study, proposed DFA model aims to categorize observations as the ones having positive or non-positive crisis indexes based on linear combinations of ten predictor variables those provide the best discrimination between groups. To identify currency crisis, exchange market pressure index (EMI) was first proposed by Girton and Roper (1977). Main weakness of EMI is that it does not consist any money market indicators, which are significant in currency crises. Therefore, in this study, currency crisis index (CI) is used to define currency crisis by adding interest rates. CI is a weighted average of change in interest rates, change in real exchange rates, and change in international reserves. The positive and negative signs of each variable indicate the expected sign of each variable before the crisis period.

$$CI_i = (\%\Delta r_i / \Delta\%\Delta r) - (\%\Delta RER_i / \Delta\%\Delta RER) - (\%\Delta IR_i / \Delta\%\Delta IR),$$

where:
- real interest rate (r): deflated using consumer prices,
- international reserves (IR): international reserves minus gold,
- real exchange rate (RER): derived from a nominal exchange rate, adjusted for relative consumer prices.

In order to measure the prediction accuracy of DFA result on crisis index determination, data set is divided into two as training data set and test data set. Discriminant function is trained and obtained the final form based on the observations of training data set. Obtained function is then used to categorize the observations of test data set into two groups based on values of their predictors. The predicted categories of test data set's observations are then compared with their actual categories, and classification model performance is then evaluated. Namely, model is labelled as good performing or accurate when it predicts positive crisis index for an observation which actually has a positive index value or non-positive crisis index for an observation actually having a non-positive crisis index value. Data of nine countries, India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Russia, Turkey and Thailand are used in model training, and remaining six countries data, Argentina, Brazil, Chile, Colombia, Uruguay and Venezuela, formed test data set. The process of research is summarized in Figure 2.

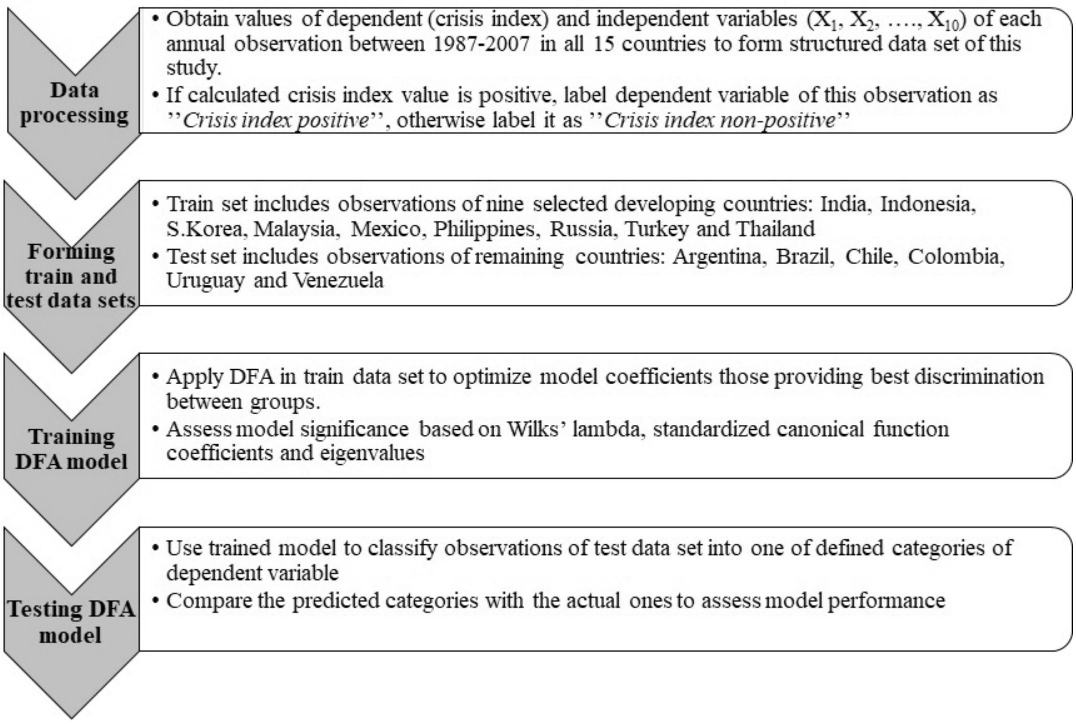

Figure 2. Summary of empirical process

Source: Authors

5.2. Descriptive Findings

Frequency and percentage distributions of number of annual observations representing positive and non-positive crisis index values for each country in training and test data sets are represented in Table 3.

From Table 3 values, it is observed that number of years that is related with positive crisis index value is generally higher in train set countries compared to test set countries. This also supports the train and test data set selection process of this study. Since catching signals of crisis are very important in model development, it was better to put those countries into training data set. In contrast to earlier studies, train data set is used to control for characteristics of currency crises in each country.

Table 3

Distribution of observations based on levels of dependent variable

Data sets	Countries	"Crisis index positive"		"Crisis index non-positive	
		Frequency (n)	Percentage (%)	Frequency (n)	Percentage (%)
Train data set	India	7	33.333	14	66.667
	Indonesia	4	19.048	17	80.952
	S.Korea	8	38.095	13	61.905
	Malaysia	10	47.619	11	52.381
	Mexico	5	23.810	16	76.190
	Philippines	11	52.381	10	47.619
	Russia	1	4.762	20	95.238
	Turkey	6	28.571	15	71.429
	Thailand	9	42.857	12	57.143
Test data set	Argentina	6	28.571	15	71.429
	Brazil	4	19.048	17	80.952
	Chile	8	38.095	13	61.905
	Colombia	4	19.048	17	80.952
	Uruguay	2	9.524	19	90.476
	Venezuela	3	14.286	18	85.714

Source: Authors' calculations

Descriptive statistics of the independent variables for the two groups (levels of the dependent variable), and the significance of mean difference between groups are presented in Table 4. Since year, last independent variable (X_{10}), is ordinal, it is not meaningful to represent related descriptive statistics.

Table 4

Test of equality of group means for the corresponding input variables

Code	Definition of input variables	Years with positive crisis indexes		Years with non-positive crisis indexes		Test statistics	
		Mean	SD	Mean	SD	t	Sig.
X_1	real interest rate (%)	8.610	13.224	7.883	15.203	−0.42	0.676
X_2	GDP annual growth (%)	5.171	4.115	3.906	4.982	2.30	0.022*
X_3	current account balance/reserves	−0.256	0.896	−0.032	0.536	−2.19	0.030*
X_4	export (% growth)/import (% growth)	−0.226	9.064	2.823	32.687	−1.28	0.200
X_5	portfolio investment/foreign direct investment (FDI)	0.552	2.493	2.388	12.245	−2.15	0.033*
X_6	M_2growth (annual %)	52.585	245.771	86.555	356.482	−0.96	0.337
X_7	domestic credit provided by banking sector (% of GDP)	74.094	49.319	58.011	41.145	2.70	0.008**
X_8	bank liquid reserves to bank assets ratio (%)	8.347	7.500	9.341	8.196	−1.03	0.305
X_9	cash surplus/deficit (% of GDP)	−0.125	2.148	−0.350	2.269	0.82	0.414

*: difference is significant in 95% CI **: difference is significant in 99% CI
Source: Authors' calculations

Table 4 shows that for mainly four of the independent variables, X_2, X_3, X_5 and X_7, differences between two groups of the dependent variable are statistically significant. For the remaining predictors no significant differences are seen between group means.

5.3. DFA Results

DFA is applied in train data set. The effectiveness of the trained discriminant model is evaluated based on eigenvalue, canonical correlation, and Wilks' lambda statistics. The eigenvalue statistic is the ratio of the between-groups to within-groups sum of squares of discriminant scores as shown in Table 5.

Table 5

Result on eigenvalues and canonical correlation

Function	Eigenvalue	% of variance	Cumulative (%)	Canonical correlation
1	1.117[a]	100.0	100.0	0.726

[a] First 1 canonical discriminant functions were used in the analysis
Source: Authors' calculations

Large eigenvalue (1.117) represents that the trained model has high discriminating ability. The canonical correlation, which is 0.726 for this data set, shows the degree of relation between discriminant scores and the groups of the dependent variable. Result on Wilks' lambda is presented in Table 6. Although, lower Wilks' lambda scores, meaning that the most of the total variability is associated to differences between the means of discriminant scores of two groups, is preferred, based on the significance value it is concluded that discrimination model is significant ($p<0.05$).

Table 6

Wilks' lambda results

Test of function(s)	Wilks' lambda	Chi square	df	Sig.
1	0.869	25.439	10	0.005

Source: Authors' calculations

Standardized canonical discriminant function coefficients are presented in Table 7. In DFA, these standardized coefficients are used to understand the relative importance of predictors in discriminating the dependent variable. Higher scores indicate higher importance of the variables. Positive or negative sign of coefficients show predictors contribute to model in opposite ways.

Table 7

Standardized canonical discriminant function coefficients

Independent variable	Function 1	Independent variable	Function 1
X_1	0.038	X_6	–0.166
X_2	0.366	X_7	0.552
X_3	-0.619	X_8	0.320
X_4	-0.156	X_9	–0.121
X_5	-0.146	X_{10}	–0.135

Source: Authors' calculations

From Table 7 values, it is observed that the highest negative coefficient of discriminant model is associated with the third independent variable, current account balance/reserves. This means that, decrease in current account balance/reserves increases the discriminant score and probability of having a positive crisis index value. Magnitudes of the other negative coefficients of X_6 (M2 growth (annual %)), X_4 (export (% growth)/import (% growth)), X_5 (portfolio investment/foreign direct investment (FDI)), X_{10} (year) and X_9 (cash surplus/deficit (% of GDP)) are decreasing in order and these predictors also decrease the discriminant score at least for some. On the other hand, model predictors X_7, X_8 and X_2 have high positive coefficients. Thus, it can be concluded that increase in values of domestic credit provided by banking sector (% of GDP), bank liquid reserves to bank assets ratio (%), and GDP annual growth (%) may increase the discriminant score and probability of being classified as "crisis index value positive". Finally, canonical coefficient of the first independent variable, real interest rate (%), is almost zero, meaning that this does not make a significant effect on discriminant score and thus discrimination.

The obtained discrimination model is then used to predict crisis index group membership of the test data set, for the six developing countries. Predicted groups are compared with the actual groups of the dependent variable. Performance results of discriminant model are evaluated based on three metrics: accuracy, sensitivity, and specificity. Model's accuracy shows percentage of correctly classified observations, where either both of the actual and predicted groups are "crisis index positive" or both of them are "crisis index non-positive". Specificity shows how well model classifies the negative observations. In this setting, negative observations show the ones in which crisis index are non-positive. The final metric is sensitivity showing the performance of the model in classifying positive observations, the ones having positive crisis index values in this study. Model performance results for each of the study data set countries, and the overall for the train and test data sets are presented in Table 8.

Table 8

Classification results on train and test data sets

Data set	country	accuracy (%)	sensitivity (%)	specificity (%)
Train data set	India	80.952	92.857	57.143
	Indonesia	80.952	88.235	50.000
	Korea	66.667	76.923	50.000
	Malaysia	52.381	18.182	90.000
	Mexico	71.429	87.500	20.000
	Philippines	66.667	60.000	72.727
	Russia	95.238	100.000	0.000
	Thailand	52.381	33.333	77.778
	Turkey	76.190	86.667	50.000
	overall	71.429	80.833	55.072
Test data set	Argentina	57.143	80.000	0.000
	Brazil	71.429	76.471	50.000
	Chile	61.905	69.231	50.000
	Colombia	66.667	76.471	25.000
	Uruguay	52.381	52.632	50.000
	Venezuela	66.667	66.667	66.667
	overall	62.698	69.697	37.037

Source: Authors' calculations

Since the optimal discrimination model is trained and obtained on training data set, performance of DFA is higher on this data set compared to test data set as expected. From the results of Table 8, it is observed that while around 71.429% of observations are correctly classified in training set, the corresponding percentage is 62.698% on test data set, showing that discriminant model performs well even in test data set. The sensitivity results showed that model predicted the 80.833% of the instances having a positive crisis index correctly in the train data set countries and the years having positive crisis index are correctly classified with 69.697% in the test data set. However, the specificity metrics are lower compared the sensitivity ones; i.e. 55.072% in the train and 37.037% in the test data set. This showed that the years having a non-positive crisis index are incorrectly classified as having a positive index.

The overall results of the train and test data sets are also obtained almost for all the study countries separately. As seen from Table 8, between the nine countries in the train data set, six of them had the model accuracy higher than 70%, and the remaining three of them (Korea, Malaysia, and Thailand) have accuracy levels varying in 50% to 70% range. Similarly, between the six countries of the test data set, four of them had a model prediction accuracy of higher than 60%, and the remaining two of them (Argentina and Uruguay) have accuracies between 50% to 60%.

Thus, the proposed DFA model is validated in 15 different countries' panel data covering 21 years period. The obtained results showed that the model is applicable for all these different cases/countries.

6. How well does this model fit the crisis experiences?

During the 1980s many developing countries implied financial liberalization. The 1991 India crises rooted in twin deficit: trade deficit and fiscal deficit. In 1994, the Mexico crisis, known as the "Tequila Effect" or "Tequilla Crisis" that started after unexpected devaluation of the peso which spread to other Latin American currencies. The 1997 Asian crisis, also called the "Asian Contagion" began in Thailand and spread to four Southeast Asian countries, South Korea, Malaysia, Indonesia, and Philippines which are at the core of the Asian crisis. In contrast to most previous episodes, this crisis is characterized by the financial sector instability and high foreign capital investments outflow. The Turkish economy also suffered from the currency crises in 1994, 1999 and 2001. The later currency crisis example is 1998 Russian crisis. All these crises had severe impacts on the neighbouring economies through different contagion channels.

As mentioned before, the input variables of the models in this study are commonly used in signal approach. The empirical findings indicate that variables including current account balance/reserves, M2 growth (annual %), export (% growth)/import (% growth), portfolio investment/foreign direct investment (FDI), cash surplus/deficit (% of GDP) have explanatory power for the currency crises in test data group of countries. On the other hand, the input variables of the models: real interest rates (%), GDP annual growth (%), domestic credit provided by banking sector (% of GDP), bank liquid reserves to bank asset ratio (%) do not have predictive power on crises.

Firstly, high foreign trade balance and current account deficit may significantly increase the foreign exchange volatility and balance-of-payment problems. Secondly, the increasing M2 growth is a result of reduced international reserves. Lastly, even developing countries have attracted high foreign capital inflow due to the high interest rates which in turn caused foreign investors outflow in the aftermath of crisis (Lang, 2013). According to the currency crisis experiences in developing countries, as highlighted in the literature, these variables also provide expected negative sign. It can be concluded that these variables have crucial signal of the emergence of currency crises.

7. Concluding remarks

All three generation currency crises models combining the signalling indicators have been transformed into empirical models mainly early warning signal approach. In this context, this study indicates that the leading indicators provided by the discriminant function analysis can be used to predict the probability of crises in other countries. When one or more leading indicators signal crisis in one country, the crisis may also spread to other crises through the contagion channels. According to the empirical findings, the variables in pre-crisis period include current account balance/reserves, M2 growth (annual %), export (% growth) / import (% growth), portfolio investment / foreign direct investment (FDI), cash surplus / deficit (% of GDP). These variables are expected to characterize pre-crisis periods with macroeconomic fundamentals. In more details, except for portfolio investment to foreign direct investment (FDI) ratio, the other input variables have negative sign due to the relation with the currency crises index. In the light of currency crises models, crises experiences show that outcome of a lending boom and high reserve loses in countries seemed to be more vulnerable to crises.

Thus, the empirical findings of this paper support evidence that currency crises are mainly related to weak macroeconomic fundamentals, parallel with the other empirical studies as well as the theoretical currency crises models. In our view, the ongoing research on forecasting model should be extended by considering the contagion channels of crises. Additional indicators could be also analyzed including political instability and financial openness. The main result indicates that the discriminant function analysis could be used complementary to early warning signal approach to enhance their predictive power.

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