Predicting Financial Crises in Emerging Markets using a Composite Non-Parametric Data Mining Model

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Abstract – *The large number of financial crises in emerging markets over the past ten years has left many observers, both from academia and financial institutions, puzzled by an apparent lack of homogenous causal relations between endogenous economic variables and the bursting of large financial shocks. The paper aims at showing that the key difficulty is not on the identification of proper endogenous variables, but on the ability to combine them in a way that is able to capture the combinatorial aspect of such causal relations. The paper is based on a newly developed non-parametric methodology for country risk signalling: the RiskMonitor CDM-Model. Using a combination of macroeconomic indicators and a composite model of 5 modern non-parametric classification methods, we constructed 9 early warning signals to predict financial crises in emerging markets. These signals are constructed for 3 types of crises (cyclical crises, exchange rate crises and transfer crises) and over 3 horizons (less than 1 year, 1 to 3 years, 3 to 5 years). This complex use of quantitative models is able to provide excellent early warning information, with impressive back-testing results on 50 developing countries over the period 1980 to 2002.*

Keywords: Financial crises, Leading indicators, Early warning systems, Classification methods, Emerging countries.

1 Introduction

The ability to provide adequate early warning signals on up-coming crises in emerging markets is a key operational input in firms' definition of their international strategies. Multinational companies as well as an increasing number of small and medium size enterprises consider that they need to increasingly target developing countries as growth drivers, but are often reluctant to do so because of a perceived risk that they cannot easily manage, i.e. country risk.

Any pretence to provide satisfactory early warning signals has first to take into account the fact that country risk is a changing concept over time, that it therefore needs a careful definition before starting the methodological research, and that such research has to bear in mind the limitations of existing approaches.

Country risk has existed since international transactions were conducted. If we limit ourselves to the recent contemporary history (i.e. since the 60s), we note three distinct phases: until the mid-70s, the major aspect of country risk was political, through repeated nationalisation or confiscation of non-residents' assets in developing countries, at a time when such assets were heavily concentrated in natural resources exploitation. From the mid-70s to the end of the 80s, a major shift occurred, in part related to the financial recycling of oil-exporting countries surpluses by western commercial banks: the period was characterised by a significant banking intermediation, where borrowers were mostly government or state owned companies in developing countries, and lenders were commercial banks, public creditors from OECD countries and multilateral institutions. After most Latin American and other developing countries defaulted on their international loans and had to restructure and reschedule their foreign debt obligations (1982-1987), a new transformation occurred through the securitisation of international finance and the related financial integration of developing countries' markets into world financial flows. 'Pure' debt crises still exist, but they are associated with other financial disruptions, including exchange rate collapse, banking crises, and domestic defaults. Moreover, the restructuring is made more complex by the proliferation of instruments, borrowers and lenders in the global financial intermediation. This third phase of country risk is still prevalent today, even tough there are growing signs of new forms of 'political' risk, either through sovereign decision on contractual agreements or through regulatory uncertainty.

Any method for country risk assessment needs there-

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fore to embrace the fact that it is a multi-facet concept: from political events to market disruption, from major shocks to benign but costly step-by-step deteriorations. Country risk today has to take into account a more volatile global financial environment and a growing international interdependence, as well as an increasing relationship between political and economic factors. Indeed, it can be argued that any political event able to have significant consequences on non-residents' assets in a developing country would be preceded by a macroeconomic deterioration (insufficient growth over a long period, excessive inflation...). This would imply that, in a first approach, we can limit ourselves to the economic and financial aspects of country risk. It can also be shown that some financial crises are always coincident: for instance, international liquidity crises (inability to meet short-term foreign currency needs by a developing country's economic agent) and the need to resort to 'crisis measures' (non-transfer of foreign currency reserves, arrears on foreign payments...) are always associated with either a default on long-term foreign currency liabilities, or an exchange rate devaluation. As indicated below, this enabled us to focus on three types of economic crises, namely solvency, exchange rate and cyclical. The definition of the 'target variable' has also to deal with the magnitude and violence of the possible changes that are announced. Indeed, there is a need not only to 'grade' risk (for example through alphabetical or numerical ratings), but also to differentitate between shocks that are so large that they can derail the best written contract or disrupt the best counterpart, and difficulties that can translate into manageable income flow or asset issues.

Finally, the research has to draw lessons from the past experiences and methods: in particular, it is very revealing that the track record of international rating agencies has been dismal over the past 15 years. This poor performances can be attributed in part to institutional constraints (impact on the markets of a major downgrading long enough in advance, with the risk of self-fulfilling prophecies); but they are also related to the characteristics of the methods used, all of them using linear combinations of a long list of economic and financial indicators. Interestingly, a recent report for the Conseil d'Analyses Economique (CAE, a think-tank attached to the French Prime Minister) stated that the same variables or economic and financial indicators could not capture the required information to provide crisis signals: each type of crisis would need a different or specific set of explanatory variables (see Boyer et al. (2004)). However, we argue in this paper that the issue is not the apparent inability of a set of indicators to be good predictor for country crises, but the ability to combine these indicators in such a way that they can capture the non-linear characteristic of the relationship between the economic environment and the occurrence of a crisis.

The paper is structured in three parts: we first describe the key characteristics of the methodology and the use of a set of non-parametric models to provide crisis signals on a sample of 50 emerging economies. We then present the statistical performances of this methodology, with an important development on the different ways to make such performance measurement. Last, we illustrate the predictive capabilities of the method through an illustration based on the Thai crisis in 1997.

2 Methodology

Numerous emprirical studies try to identify the causes of economic and financial crises in emerging countries: Krugman (1979), Obstfeld (1994), Cantor and Packer (1996), Eichengreen et al. (1996), Frankel and Rose (1996), Goldstein (1996), Goldstein and Turner (1996), Kaminsky and Reinhart (1999), Komulainen and Lukkarila (2003) as well as to develop leading indicators: Diebold and Rudebusch (1989), Stock. and Watson (1989), Kaminsky et al. (1997). Our methodology aims to contribute to this literature with two objectives. The starting point of our methodology is a precise definition of three types of difficulties or shocks that can affect international operations, namely solvency issues, exchange rate risks and cyclical reversal risks. The second starting point is the willingness to distinguish between a measure of 'economic quality', a synthetic rating enabling a hierarchal positioning of countries according to risk in different areas, and signals of upcoming shocks that would be large enough to derail indiscriminately individual contracts and counterparts. We like the image of a skier in front of a foggy slope: he wants to assess the risk of going down, and surely would like to know whether the ski-run is bumpy, irregular, steep or rather flat; but he would also want to know with the greatest degree of certainty if there is a deep ravine in the middle of his foggy route. The ravine is a 'full-blown crisis', and the characteristics of the ski-run are the synthetic 'economic quality measures'. With such objectives defined as our 'targets', the proprietary methodology that is behind our RiskMonitor service includes the three following principles: (1) a risk measured as a non-linear result of economic and financial circumstances, (2) a methodology combining quantitative results obtained from a sophisticated numerical system and qualitative analyses and (3) a transparent and understandable diagnostic process.

RiskMonitor is based on the realisation that country risk is a result of non-linear combinations of economic and financial circumstances, with threshold effects on sensitive indicators. Indeed, academic research on risks (not only country risk, but also counterparty risk or market risk) has consistently demonstrated that it is not necessary to use a very large number of economic or financial indicators to capture most of the required information about risk, but that the combinatorial fea-

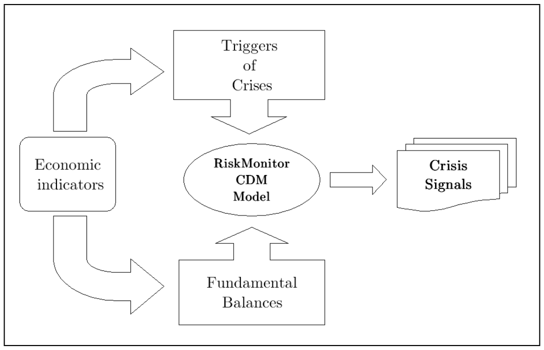

Figure 1: RiskMonitor Methodology

tures of a limited number of variables was the core element for risk materialisation. etc...)

We use twelve macroeconomic and financial indicators as input variables of our early warning signals. Each variable is a rather complex computation of simple and standard macroeconomic indicator, calculated on 50 developing countries using official quarterly and annual data from 1970 to 2002, and are very straightforward to understand and assess: for example, we use a variable for 'economic growth', which is computed as the per-capita GDP growth at constant prices with an accelerator (decelerator) effect.

From these twelve indicators, we derive two country risk measures. One the one hand, using a normative approch, we compute non-linear scores (one per Fundamental Balance) and then country risk Ratings. These country risk Ratings are statistically optimized against observations of exchange rate depreciation and poor economic performances, through a genetic algorithm. On the other hand, we use a classification algorithm, the composite non-parametric data mining model (the CDM-Model), that give an early country crisis signal.

The combinatorial and threshold effects are integrated by grouping the indicators two-by-two to construct six Fundamental Balances. Each Fundamental Balance is describing a specific set of 'circumstances', and the ability to see the movements and position of a country in such circumstances is providing the key inputs for our country risk measures. For each variable, a risk threshold is determined through a statistical analysis.

The first Fundamental Balance, the Growth Balance, measures the ability of a country to register sufficient economic growth without triggering unsustainable external imbalances. The second, the Debt Balance, measures the structural quality of a country's external financing and its ability to balance debt with more stable inflows of direct investment. The Liquidity Balance assesses the foreign currency situation of a country by looking at the relative level of currency reserves and the vulnerability related to the accumulation of short-term foreign currency liabilities. The Foreign Exchange Balance looks more precisely into a key financial aspect of the country risk by measuring the relative valuation of the exchange rate in terms of international competitiveness as well as the dynamics in official foreign currency reserves against international interbank lending and domestic monetary aggregates. The Cyclical Balance gives a view of the cyclical position of the country in a country risk perspective, and allows a measure both of the quality of the domestic economic policy and of the nature of the most sensitive risks, by looking at the de facto stance of the monetary policy and the momentum of domestic activity. Our indicators have a 3-6 quarters lead on actual evolutions. The Banking System Balance gives a measure of the risks associated with imbalances in the overall banking situation of the country, through an appreciation of the links between activity and banks' health on one hand, and the dependence of domestic banks on foreign financing on the other hand.

In the rest of the paper, we present only the methodology for early warning signals.

3 Data

All data used to estimate the early warning signal is derived from the indicator developed for the RiskMonitor methodology. These indicators are calculated on 50 developing countries (the list of countries is presented on table 1), over the period 1980 to 2002. We use quarterly and annual data from well-known internatinal organisations (IMF, World Bank, United Nations, OECD, BIS,...). This is a key element as we need homogeneous and comparable indicators over the 50 countries that the methodology covers. As we use only 'official data', the methodology must take into account the fact that these data are available only after a time lag that can vary over countries and variables. A lot of research has been done on the choice of leading indicators for early warning system of country crises (see Kaminsky et al. (1997)). We present on the table 2 the twelve macroeconomic indicators that we use as inputs, or 'patterns', for our early warning system. As we work on developing countries, a lot of data are missing and 'strange' value have sometime to be corrected. All the data that we use is also normalised.

But if these macroeconomic indicators are useful to characterise the patterns of a developing country at a moment, we also need the target variables that will allow our early warning system to learn from the past country crises to predict future crises. To prepare these new time series that will 'lead' the supervised learning of our algorithms, we create nine triggers for the country crises that we want to predict. These triggers are defined boolean times series ('true' for a crisis and 'false' for a stability period) for three types of country crises: cyclical crises, exchange rate crises and default crises. The triggers for the cyclical crises are calculated

Indicator	**Periodicity**	**Description**
Economic growth	annual	GDP growth
External balance	annual	External balance sustainability
Financing stability	annual	Stability of FDI inflows
Debt service	annual	External financing
Forex liquidity	quarterly	Foreign currency situation
Maximum potential service	quarterly	Short-term foreign currency liabilities
Forex reserves quality	quarterly	Dynamics in forex reserves
Exchange rate competitiveness	quarterly	International competitiveness of exchange rate
Monetary pressure	quarterly	Quality of monetary policy
Real economic pressure	quarterly	Momentum of domestic activity
Domestic leverage	quarterly	Activity and banks' health
Foreign financing	quarterly	Dependence on foreign financing

Table 2: Twelve macroeconomic indicators taken from the RiskMonitor Fundamental Balances.

Zone	**Country name**
North Africa	Algeria, Egypt Morocco, Tunisia
Africa	South Africa, Cameroon Ivory Coast, Ghana Kenya, Nigeria Congo
Latin America	Argentina, Brazil Chile, Colombia Ecuador, Mexico Peru, Uruguay Venezuela
Asia	China, Korea Indonesia, Malaysia Philippines, Taiwan Thailand, Vietnam
Indian-Sub-continent	Bangladesh, India Pakistan, Sri Lanka
Europe	Bulgaria, Hungary Poland, Czech Rep., Romania, Turkey
Formet Soviet Union	Croatia, Kazakhstan Lithuania, Russia Ukraine
Middle-East	Saudi Arabia, Bahrain UAE, Iran Israel, Jordan Oman

Table 1: List of countries included in the RiskMonitor CDM-Model

as negative real GDP growth rate associated with a very sharp decrease (over 7%) of this growth rate from the previous year. The triggers for the exchange rate crises are calculated as high depreciation rate of the real exchange rate against USD (20% or more over one quarter, 30% over two, 40% over three and 50% over four). Finally, the triggers for default crises are calculated using documents from the Institute For International Finance (IIF). Then, using these triggers, $T(t, \theta)$, we create the 'pre-crises' variables, $C(t, \theta, h1, h2$, that will monitor at a date t, if there is a crisis between $h1$ and $h2$.

$$C(t, \theta, h1, h2) = max\left[T(t + h1, \theta), ..., T(t + h2, \theta)\right] \quad (1)$$

We then obtain a total number of nine 'pre-crises' variables.

Using the two sets of variables, the patterns (the RiskMonitor macroeconomic indicators) and the targets (the 'pre-crises' variables), we are able to create our classification algorithm. The classification algorithm that we choose to use, the CDM Model, is presented in the next section.

4 Model

One of the main result of our investigations to find a good classification system to predict country crises in developing countries is that modern classification methods could produce powerful early warning signals, but that there are always difficulties when using only one methodology. The difficulty is not always the same but all the methods have their own positive and negative aspects. Neural networks are often cited as being 'black-boxes' and difficult to train, Support Vector Machines (SVM) are less performant and more difficult to optimise, recursive partitioning are easy to understand but not as powerful as neural networks... At the begining of our research, the idea was simply to overcome the 'black'box' difficulty of neural networks and to try to find signals that we would be as good as a neural network but with a confidence index or something that would help us to understand the reasons for a crisis signal. We finally discovered that combining a small number of modern classification algorithms could produce a more powerful and stable system and would give us a confidence index when raising a signal of crisis in a country.

The RiskMonitor CDM Model is a composite nonparametric data mining model. This model is estimated using a combination of five modern classification algorithms selected over a wide range of classification methods. The five selected classificaton algorithms are: a neural network, a SVM, a recursive partioning, a random forest and a bagging algorithm. All these algorithms produce a diagnosis using a different technique. Most of these techniques have been applied to several fields with success: medical diagnosis, genetics, cancer, speech recognition, military defense, ... These algorithms were selected over a range of more than 15 classification methods, allowing linear or non linear combinations of patterns and using supervised or unserpervised learning (ie: with predefined groups or not). The most popular of the tested algorithms were: various combination of linear discriminant analyses combined with principal components analyses, Logit and Probit models, k-means classifications, k-nearest neighborough, different types of support vector machines, self organizing maps, learning vector quantization, different types of neural networks,... All these models were estimated using 10 random sub-samples of the overall dataset of 50 countries over the period 1980-2002. We used a *10*-fold cross validation procedure to select the five models that give the best early warning signals out of sample. These models were then estimated using the overall sample, and not only a subset of these sample of countries. As we only have a small number of country crises into our sample, we had to choose this procedure to be sure not to forget any type of crisis during the final estimation.

Formerly, the CDM-Model is a sum of the diagnosis of the diagnosis of the underlying models. Using n previously selected classification models M_i, the diagnosis at time t, for a country crisis of type θ on the horizon betwen $h1$ and $h2$ is given by our model using the following formula:

$$CDM(t, \theta, h1, h2) = \frac{1}{n} \sum_{i}^{n} M_i(t, \theta, h1, h2) \qquad (2)$$

If the value of CDM is zero, then we have a stability signal for the country on the horizon measured. If we have instead a postive value, there is a crisis signal, with a confidence index of CDM, where n is the number of classification models that we use. In the case of our early warning signal on country crises, we selected five classification algorithms. The purpose of this paper is not to present in detail all of these five methods but only an application of a combination of these models into a composite one, to country risk analysis. Nevertheless, we comment each of the models very rapidly below.

The first model selected is a neural network. A neural network is a system composed of simple connected elements. It has the capacity to learn experiential knowleadge through a structure of nodes, weights and simple functions. Neural networks are well-known to be able to detect complex structures in large datasets (see Ripley (1996) and Venables and Ripley (2002)). In the case of the CDM-Model we use a three layers MLP (Multi-Layers Perceptron) with twelve input neurons (the twelve macroeconomic indicators) and 1 output neuron (the 'pre-crisis' concerned by the learning process). A neural network produce a target (an estimated signal of crisis or not) from patterns (observed values of our macroeconomic indicators) using the following formula:

$$\hat{C} = \sum_{j} \left(\hat{\omega}_j + \hat{\gamma}_j F(\sum_{i=1}^{12} \hat{\alpha} + \hat{\beta}_i X_i) \right) \qquad (3)$$

and the activation function in our case is a sigmoid:

$$F(n) = \frac{1}{1 + e^{-n}} \qquad (4)$$

where I are the twelve macroeconomic indicators (the patterns) and $\hat{C}$ the estimated 'pre-crisis' variable (the target). The algorithm is an optimisation process that will estimate the values of $\hat{\omega}$, $\hat{\gamma}$, $\hat{\alpha}$ and $\hat{\beta}$ under the constraint:

$$min(|C - \hat{C}|) \qquad (5)$$

This kind of neural networks is very powerful to detect non-linear patterns that are too complex to be analysed using a traditional statistical tool.

The second classification algorithm selected is a Support Vector Machine (SVM). SVM are kernel based learning algorithms that are often cited to be good alternative to neural networks when the 'black-box' aspect of neural networks is a problem. These methods allow to capture complexe structure in dataset by mapping the training vector into a higher dimensional space. These algorithms allow to classify non-linear data using a linear separation on hyperplans through a kernel function Φ. Different kinds of SVM are available, from simple classification SVM to regressors (see Boser et al. (1992) and Vapnik (1995) for details). In the case of the CDM-Model, we chose regressors:

$$f(x_i) = \sum_{i=1}^{n} w_i \Phi(x_i) + b \qquad (6)$$

with radial basis kernel function (RBF) of the form:

$$\Phi(x)\Phi(y) = k(x, y) = e^{-a||x-y||^2},\ a > 0 \qquad (7)$$

The third model that we selected is a recursive partitioning. Recursive partitioning is an algorithm that creates trees using simple criteria, to classify the dataset into various subsets. The idea behind recursive partitioning is to binary split the input dataset using nodes and by using thresholds values (α) on patterns (x_i) to search for relationships in the data. The following formula is an example of binary splitting the node $N(1)$ into two child-nodes $N(1,1)$ and $N(1,2)$ using a criterion on the value of the variable x_i.

$$N(1) = \begin{cases} x_i \geq \alpha & N(1,1) \\ x_i < \alpha & N(1,2) \end{cases} \tag{8}$$

This kind of algorithms is particularly well suited to find non-linear and hidden structures in datasets (see Breiman et al. (1984)) and the trees created allow to understand the path to the early warning signal using simple thresholds.

We selected Random Forest as our fourth model. Random forests are probably among the most powerful and promising classification technologies available at the moment we write this paper. This is one of the very last creation of Breiman (see Breiman (2001)). The idea behind this classification method is still the tree, but this time we don't produce one tree but forest of classification trees. To classify a new object, we input this object into each tree, and each one give a classification. We retain the classification that as the majority of 'votes'.

The fifth model is a Bagging classification methodology, that is derived from recursive partitioning and were introduced by Breiman (1996). This is a refinement of the kind of trees where multiple trees are generated using boostrap samples. A 'voting' strategy is used to obtain the classification.

In the next section, we present the results obtained using the CDM-Model to predict country crises through the period 1980 to 2002 on 50 developing countries.

5 Results and illustration

In this section we first present the standard to assess the quality of classification algorithms, we then present the results obtained using standard classification methods and we compare these results to those obtained with the CDM-Model. Finally, we illustrate the power of the methodology using the case of Thailand financial crisis of 1997.

We usually evaluate the performances of classification algorithms using a confusion matrix like the one shown on table 3. Using this kind of matrix, we can compute many indicators that measure the power of a diagnosis system. None of them is a good measure of the power of a system and it is always needed to monitor more than two ratios to evaluate the quality of a diagnosis system. The two most common measures are the sensitivity and the specificity. The sensitivity represents the percentage of crises covered by the signal, or the probability of the signal to find a crisis signal among the observations of crisis. This is a 'crises cover-ratio'.

$$Sensitivity = 100 * \frac{A}{A+C} = 100 * \frac{TP}{TP+FN} \tag{9}$$

The specificity represents the percentage of stability periods covered by the signal, or the probability of the signal to find a stability signal among the observations of stability. This is a stability cover-ratio.

$$Specificity = 100 * \frac{D}{D+B} = 100 * \frac{TN}{TN+FP} \tag{10}$$

In the case of the CDM-Model, the positive probability value (PPV), that is the percentage of true crisis signals is also useful. This is the percentage of realised crisis when a crisis is predicted by the signal : a confidence indicator of the crisis signals.

$$PPV = 100 * \frac{A}{A+B} = 100 * \frac{TP}{TP+FP} \tag{11}$$

The negative probability value (PPV) is the percentage of true stability signals. This is the percentage of stability periods when no crisis is predicted by the signal ; a confidence indicator of the stability signals.

$$NPV = 100 * \frac{D}{D+C} = 100 * \frac{TN}{TN+FN} \tag{12}$$

The accuracy is useful for a single measure of performances if the sample is uniformly distributed between crises and stability periods. It is calculated as the percentage of good classification of crisis and stability signals among observations.

$$Accuracy = 100 * \frac{A+D}{A+B+C+D} \tag{13}$$

The error rate (ER) is calculated as the percentage of misclassification of crises and stability periods.

$$ER = 100 * \frac{B+C}{A+B+C+D} = 1 - Accuracy \tag{14}$$

Finally, the percentage of crises (PC) is calculated as the number of crises over the sample.

$$PC = 100 * \frac{A+C}{A+B+C+D} \tag{15}$$

Before presenting the results obtained with our model, let us go back on a key point to take into account when evaluating the power of a classification algorithm. A key question to ask is: what can be said without a classification model ? If making a prediction of the probability of crisis on a country without a model, only using a pure uniform random indicator, it will give 50% of the time a 'crisis signal' and 50% of the time a 'no crisis signal'. The confusion matrix of such a 'naive model' is presented on table 4. We can easily compute some of

	Crisis observed	**No crisis observed**
Signal of crisis	A = True Positive (TP)	B = False Positive (FP)
No signal of crisis	C = False Negative (FN)	D = True Negative (TN)

Table 3: Confusion matrix used to evaluate a classification algorithm into two groups.

	Crisis observed	**No crisis observed**
Signal of crisis	$(1000 * 50\%) * 10\% = 50$	$(1000 * 50\%) - 50 = 450$
No signal of crisis	$(1000 * 50\%) * 10\% = 50$	$(1000 * 50\%) - 50 = 450$

Table 4: Confusion matrix of a naive model over 1000 observations and with a percentage of crises of 10%.

Horizon	**Model name**	**Sensitivity (%)**	**PPV (%)**	**Accuracy (%)**
less than 1 year	LDA	7.7	54.5	94.1
1-3 years	LDA	12.9	46.8	86.9
3-5 years	LDA	12.5	52.8	88.2
less than 1 year	Logit	-	-	-
1-3 years	Logit	9.1	61.9	87.6
3-5 years	Logit	4.5	43.5	87.9
less than 1 year	SVM	18.1	84.8	94.9
1-3 years	SVM	31.7	91.9	90.9
3-5 years	SVM	26.8	96.8	91.2
less than 1 year	KNN	91.6	92.8	99.1
1-3 years	KNN	92.3	94.0	98.3
3-5 years	KNN	92.9	90.8	98.0
less than 1 year	CDM-Model	87.1	100.0	99.2
1-3 years	CDM-Model	89.2	98.1	98.4
3-5 years	CDM-Model	93.3	100.0	99.2

Table 5: Signaling power on Cyclical Crises of different models using supervised learning over the sample of 50 countries covered by RiskMonitor, with more than 2000 observations and with percentage of crises from 6% (less than one year) to 12% (3-5 years).

Horizon	Model name	Sensitivity (%)	PPV (%)	Accuracy (%)
less than 1 year	LDA	0.7	16.7	94.6
1-3 years	LDA	6.1	46.7	90.0
3-5 years	LDA	-	-	90.4
less than 1 year	Logit	-	-	-
1-3 years	Logit	1.3	100.0	90.2
3-5 years	Logit	-	-	-
less than 1 year	SVM	19.1	100.0	95.7
1-3 years	SVM	34.2	97.5	93.4
3-5 years	SVM	34.6	100.0	93.8
less than 1 year	KNN	90.1	85.8	98.7
1-3 years	KNN	94.3	93.5	98.8
3-5 years	KNN	91.8	91.8	98.4
less than 1 year	CDM-Model	97.2	100.0	99.9
1-3 years	CDM-Model	97.8	100.0	99.8
3-5 years	CDM-Model	91.8	99.4	99.2

Table 6: Signaling power on Exchange Rate Crises of different models using supervised learning over the sample of 50 countries covered by RiskMonitor. with more than 2000 observations and with percentage of crises from 5% (less than one year) to 10% (3-5 years).

Horizon	Model name	Sensitivity (%)	PPV (%)	Accuracy (%)
less than 1 year	LDA	-	-	96.5
1-3 years	LDA	-	-	94.8
3-5 years	LDA	3.8	20.0	94.6
less than 1 year	Logit	-	-	-
1-3 years	Logit	-	-	95.0
3-5 years	Logit	1.3	25.0	95.1
less than 1 year	SVM	2.9	100.0	97.0
1-3 years	SVM	25.5	100.0	96.4
3-5 years	SVM	46.2	97.3	97.3
less than 1 year	KNN	85.5	79.7	98.9
1-3 years	KNN	93.6	93.6	99.4
3-5 years	KNN	88.5	93.2	99.1
less than 1 year	CDM-Model	95.7	100.0	99.9
1-3 years	CDM-Model	94.7	100.0	99.7
3-5 years	CDM-Model	94.9	100.0	99.8

Table 7: Signaling power on Default Crises of different models using supervised learning over the sample of 50 countries covered by RiskMonitor. with more than 1600 observations and with percentages of crises from 3% (less that one year) to 5% (3-5 years).

Year	Less than 1 year	1-3 years	3-5 years
1992-1	s	s	s
1992-2	s	s	s
1992-3	s	s	
1992-4		s	**C**
1993-1	s	s	**C**
1993-2	s	s	**C**
1993-3	s	s	**C**
1993-4	s	s	**C**
1994-1	s	s	**C**
1994-2	s		**C**
1994-3	s		**C**
1994-4	s	**C**	**C**
1995-1	s	**C**	
1995-2	s	**C**	
1995-3	s	**C**	s
1995-4	s	**C**	s
1996-1	s	**C**	s
1996-2		**C**	s
1996-3		**C**	s
1996-4	**C**	**C**	s
1997-1	**C**		s
1997-2	**C**		s
1997-3	**C**	s	s
1997-4	**C**	s	s
1998-1			s
1998-2		s	s
1998-3		s	
1998-4		s	s
1999-1		s	s
1999-2	s	s	s
1999-3	s	s	s
1999-4	s	s	s

Table 8: Signals of crisis of the CDM-Model on Thailand, before the financial crisis of 1997. 's' for stability within the horizon and 'C' for a crisis signal.

the ratios presented in the previous paragraph, to evaluate the predictive capacity of this naive random crisis signal. The sensitivity is equal to $50/(50+50) = 50\%$, the PPV is $50/(50+450) = 10\%$ and the probability of crisis is $(50+50)/1000 = 10\%$. We see that the quality of true crisis signals are equal to the probability of crisis within the sample. It is therefore crucial to compare the quality of the signal (the 'true crisis signal') with the percentage of crises of the sample selected: how many time is the signal better than the probability of crisis of the sample ?

We did the same test procedure over the 3 types of crises and 3 horizons covered using four different types of models: a linear discriminant analysis (see Burkart and Coudert (2002) for an application of LDA to indicators of currency crises in emerging countries), a Logit model (see Komulainen and Lukkarila (2003) for an application of Logit/Probit models to financial crises in emerging markets), a support vector machine classification (SVM) and a k-nearest neighbour classification (KNN). Tables 5, 6 and 7 show that a standard classification algorithms is not able to identify a combination of indicators that gives a good sensitivity associated with a high PPV (true signals of crises). The accuracy is usually good because a very large number of observations are classified as stable periods and the probability of crises is low. Even a Support Vector Machine with a 'C-classification' algorithm, which is usually a good alternative to neural networks, doesn't give the very good results that we usually expect from this kind of classifications. We need to introduce the a k-nNearest neighbour classification to obtain a good sensitivity associated with a high percentage of true crisis signals. These results mean that in most of the cases, cyclical, exchange rate and default crises in developing countries are not associated to simple linear combinations of macroeconomic indicators (e.g. the bad results obtained with the LDA or the Logit models) but that indeed non-linear combinations of these indicators exists, which are able to capture these risky positions (i.e. the better results obtained by a 'C-classification' SVM and a k-nearest neighbourg algorithm).

When we compare all these results to those obtained from the CDM-Model with a threshold of 3, we find that the mix of these 5 classification system gives better results. We choose a confidence degree of 3 to 5 (when 3 of the 5 classification models give a crisis signal on a country, the CDM-Model gives a crisis signal). We obtain a signal that outperform all of the other. The sensitivity of the signal is always excellent, and rarely below 90% (only on Cyclical Crises 'less that one year' and 1-3 years) and the accuracy of the signals is always bery good (rarely below 95%). A very important point is that all these figures are obtained on a sample where the probabilities of crisis is very low (maximum 12%). We can conclude that this model is ten times (or more) better that a 'naive random' model when it produces a crisis signal and that this signal covers most of the crises. In the next paragraph we give a concrete example of the power of the country crisis signal of this model.

As an illustration we present the case of Thailand's financial crisis of 1997. Despite occasional financial turbulences during 1996 and early 97, investors and bankers were still convinced that Thailand would avoid any brutal adjustment, in particular for its semi-fixed exchange rate regime. International rating agencies fueled this positive feeling by keeping the country's long-term sovereign foreign currency rating at a clear 'investment grade' level (A- until September 1997 for Standard & Poor's). However, on July 2, 1997, the exchange rate policy was abandonned and the Thai Baht lost 83% over the following 6 months. In table 8 we present the historical value of the crisis signal on exchange rate crises produced by the CDM-Model in Thailand, 5 years before the occurence of the crisis (mid 1997). At the beggining of 1992, no crisis signal is produced and the small 's' on all of the three horizons denotes a predicted stability of the economic situation over the next years. But at the end of 1992-Q3, the 3-5 years stability signal disapeer and only a quarter after that, in 1992-Q4 a 'C' signal for a exchange rate crisis over the horizon 3 to 5 years. Then, there is a very clear relay of the 1 to 3 years crisis signal (1994-Q4) and even of the less than one year crisis signal (1996-Q4).

6 Conclusion

In this paper, we presented a new methodology of early warning signal for country crises in developing countries developed by TAC. This new methodology, the RiskMonitor CDM-Model, is able to provide excellent early warning information, with impressive back-testing results on 50 developing countries over the period 1980 to 2002.

The power of this methdology is not limited to country risk analysis and could be applied to other fields of the macreconomic analysis, finance and even medical diagnosis. But more investigations need to be done to understand the model itself. First, the distance from a stability to a crisis signal is not well understood and it's quite difficult to evaluate the proximity of a signal. The Ratings that TAC developed using the RiskMonitor methodology explain a part of this, but a large amount of the non-linear macroeconomic conditions that explain the 'distance to signal of crisis' are not yet properly understood.

The second element of further interest would be the ability to recognise the exact type of exchange rate, cyclical or default crisis that is predicted. More than the horizon or basic type of crises, it would be helpful identify, for a given country, if the next crisis will be a 'Mexico-type' crisis, a 'Asian-97' one of a 'Russian' crisis. TAC already developed self-organizing maps that are able to find non-linear proximities in case of crisis diagnosis, but more investigations need to be done to create a robust methodology.

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