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AND ECONOMIC DOWNTURNS:
A COMPARISON ANALYSIS BETWEEN COST-SENSITIVE
LEARNING AND MARKOV-SWITCHING APPROACHES**

**Meriem Djennas, Mohamed Benbouziane
and Mustapha Djennas**

Working Paper No. 729

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Abstract

This paper examines the effects of macro-financial vulnerabilities on economic downturns in North Africa and GCC countries based on a Financial Stress Index (FSI). The paper identifies episodes of financial turmoil according to FSI values, and proposes an analytical framework to assess the impact of financial stress on economic downturns by using two approaches: a Cost-sensitive learning neural network and a Markov-switching time-varying model. It concludes that episodes of financial stress can be identified clearly by the two methods in a cooperative but not competitive way.

JEL Classifications: E32 - E37 - C45 - C58

Keywords: Macro-financial vulnerabilities, Economic downturn, Early warning systems, Financial Stress.

ملخص

تبحث هذه الورقة في آثار الضعف المالي الكلي على الانعكاسات الاقتصادية في شمال أفريقيا ودول مجلس التعاون الخليجي على أساس مؤشر الضغوط المالية (FSI). وتحدد الورقة حلقات من الاضطرابات المالية وفقا لقيم FSI، وتقترح إطارا تحليليا لتقييم تأثير الضغوط المالية على الانعكاسات الاقتصادية باستخدام نهجين: شبكة التعلم من حيث التكلفة ونموذج ماركوف لتبديل الوقت المتفاوتة. تخلص الورقة إلى أنه يمكن التعرف على حلقات الضغوط المالية بوضوح من خلال الطريقتين بشكل تعاوني وليس تنافسي.

1. Introduction

The last global financial turmoil has prompted policy makers and economists around the world to pay closer attention to the linkages between financial system risks and economic activity. Against this situation, many countries have developed some Financial Stress Indexes to monitor the risks in their financial systems and to gain a deeper understanding of the causes and consequences of these risks. Hence, the recent financial crisis and the associated decline in economic activity have raised some important questions about economic dynamics and its links to the financial sector.

This paper studies the relationship between macro-financial vulnerabilities and economic downturns in the region of North Africa and GCC countries by introducing a synthetic index of financial stress to monitor the financial vulnerabilities and crisis and by demonstrating how stress interacts with economic activity. We examine a variety of questions including the implications of financial stress for the economic dynamics in the considered regions; and the implications of shocks to the economic dynamics for financial stress.

Also, a parameterized multivariate and a time-varying transition probability Markov-switching model and a Cost-sensitive learning vector quantization model are estimated in order to evaluate the probability of observing a future crisis given the information contained in the set of financial variables; and consequently, make some comparisons between the two approaches in term of efficiency.

In this paper, we will try to give some answers to the following questions: Do macro-financial variables and economic downturns have symmetric effects? Do financial vulnerabilities have an impact on the economic activity in the North Africa countries and GCC countries? Does monetary policy have the same effect on the economic dynamics in the low financial stress regime and in the high financial stress regime? Could we consider the financial stress index as an efficient approach to predict the financial crises?

2. Measuring Financial Stress

2.1 Conceptualizing the Financial Stress Index

Financial Stress Index (FSI) is the subject of a rich literature. An important number of theoretical and empirical works have been developed in diversified ways in terms of approaches and tools used. The most important of these are: Eichengreen and Rose (1999); Glick and Rose (1999); Caramazza, Ricci, and Salgado (2000); Fratzscher (2000); Forbes (2001); Van Rijckeghem and Weder (2001); Kaminsky and Reinhart (2003).

In this paper, the FSI for each country¹ is constructed as a variance-weighted average of three sub-indices, which can be thought of being associated with banking, securities, and foreign exchange markets (Balakrishnan *et al.* 2009). There are many other potential candidates for inclusion in the FSI, but given the cross-country nature of this study, one objective was to use a uniform set of time series across all 11 countries. Another objective was to use a minimum set of time series that would signal financial stress episodes. Adding tends to be restrictive owing to data availability, both across time and country dimensions. It could also potentially contaminate the FSI with noisy indicators (Cardarelli *et al.* 2010).

The advantage of utilizing such an index is its ability to identify the beginning and peaks of financial stress episodes more precisely, that is, the specific quarter of a year when an episode can be said to have begun, and its duration. Moreover, constructing such an index facilitates the identification of four fundamental characteristics of financial stress events: The exchange market pressure index, sovereign debt spreads, beta banking sector, stock market returns and

¹ We consider two sets of countries: GCC (UAE, Saudi Arabia, Bahrain, Kuwait and Qatar) and NA-SA-TU (Turkey, South Africa, Morocco, Egypt and Tunisia).

finally stock volatility. Looking at these sub-components can help identify which types of financial stress (banking related, securities market related, currency related, or a combination of these) have been associated with larger output consequences (Cardarelli *et al.* 2010).

This section follows Balakrishnan *et al.* (2009) work in describing the components and methodology used to construct the FSI for considered countries. Each component is demeaned and normalized by its standard deviation, and then added together to construct the index. Normalizing each component by its standard deviation is necessary to ensure that the overall index is not dominated by large fluctuations in one component. The additive feature of the index allows for a straightforward decomposition into contributions of each component (Moriyama 2010; Cardarelli *et al.* 2010).

Episodes of financial stress are identified as those periods when the index for a country is more than one standard deviation above its trend. The FSI is given by the sum of the five components: the EMPI, sovereign spreads; the beta-banking sector, stock returns, and time-varying stock return volatility:

$$FSI = EMPI + \text{Sovereign spreads} + \beta\text{-banking sector} + \text{Stock returns} + \text{Stock volatility} \quad (1)$$

2.1.1 Variables description

An **EMPI** increases as exchange rate depreciates or as international reserves decline, where the **EMPI** for month t is given by the following formula:

$$EMPI_t = \frac{\Delta e_t - \mu_{\Delta e}}{\sigma_{\Delta e}} - \frac{(\Delta RES_t - \mu_{\Delta RES})}{\sigma_{\Delta RES}} \quad (2)$$

Δe and ΔRES are the month-over-month percent changes in the nominal exchange rate vis-à-vis an anchor currency (for example, US dollar or Euro) and total reserves minus gold, respectively. μ and σ denote the mean and standard deviation of the relevant series, respectively, over the sample period.

Sovereign spreads indicate increased (external) default risk of a country defined as the bond yield minus the 10-year United States Treasury yield using JPMorgan EMBI Global spreads². When EMBI data were not available, five-year credit default swap spreads were used.

The **β -banking sector** is derived from the standard capital asset pricing model (CAPM³):

$$\beta_t = \frac{Cov(r_t^M, r_t^B)}{\sigma_M^2} \quad (3)$$

r represents the year-over-year banking or market returns, computed over a 12-month rolling window. If $\beta > 1$ then banking sector stocks are moving more than proportionately with the overall stock market suggesting that the banking sector is relatively risky and is associated with a higher likelihood of a banking crisis.

Stock returns are a proxy to capture that falling equity prices correspond to increased market stress, where the returns are the month-over-month real change in the stock index multiplied by -1, so that a decline in equity prices corresponds to increased securities market related stress.

Stock volatility represents financial uncertainty. Higher volatility captures heightened uncertainty in an economy, derived from a GARCH specification, using month-over-month

² <http://www.bloomberg.com/>

³ The capital asset pricing model (CAPM) is used to determine a theoretically appropriate required rate of return of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset's non-diversifiable risk. The model takes into account the asset's sensitivity to non-diversifiable risk (also known as systematic risk or market risk), often represented by the quantity beta (β) in the financial industry, as well as the expected return of the market and the expected return of a theoretical risk-free asset.

real returns modeled as an autoregressive process with 12 lags (Moriyama, 2010; Balakrishnan *et al.* 2009).

Given the availability of data, we consider quarterly data from 2001 to 2010 (for FSI and Markov-switching time-varying model) and monthly data from 2000 to 2010 (for Cost-sensitive learning neural network).

On the whole, it seems that the GCC countries were more resistant to macro-financial vulnerabilities than North Africa countries, South Africa and Turkey, especially during the last world financial crisis. More presented data about GDP growth in the next sections confirm this result.

2.2 Episodes of financial stress

By considering episodes of financial stress, we are trying to decompose the sample data into two sets: periods leading to a crisis (crisis and/or economic downturn), and periods characterized by a relative financial stability (tranquil times) in terms of the degree of fragility of the economy.

Using the five sub-components described above, the FSI is constructed for each of the 11 countries in the sample. Episodes of financial stress are identified as those periods when the index for a country is more than one standard deviation above its trend (Cardarelli *et al.* 2010). These episodes signal that one or more of the banking, securities and/or foreign exchange market sub-components has shifted abruptly. Also, episodes with more than 15 standard deviation above its trend are considered as high financial stress episodes.

Overall the period sample data, we have identified 23 financial stress episodes for North Africa countries, South Africa and Turkey (NA-SA-T) and only 14 financial stress episodes for the GCC countries (Table 1). Of these episodes, 22 were considered as financial crisis with a high FSI (15 for NA-SA-T and 7 for the GCC). Most of the financial stress episodes are driven by stress in the banking sector (the banking variable accounted for the majority of the increase of the FSI during these episodes).

For the global financial crisis, the FSI indicates that the financial crisis had a significant global dimension, affecting virtually all countries in the sample (Figure 1 and 2). In addition, the FSI has accurately determined the 2000-2001 Turkish crises. Overall, the index appears to capture extreme financial episodes accurately.

The FSI also accurately captures the fact that while the origins of the current episode were in the banking sector, by early 2008 the crises had become much more broad based, affecting banking, securities and foreign exchange markets at the same time (Figure 1 and 2).

Overall, these results suggest that the FSI can be considered a comprehensive indicator that successfully identifies the main episodes of financial stress for the sample of countries under consideration and can provide the basis for an examination of the macroeconomic consequences of such stress.

3. Financial Stress and Economic Downturns

3.1 Economic downturns cycles

Having identified episodes of financial stress, a first question of interest is: How many of these episodes were followed by an economic downturn? Were economic downturns preceded by episodes of financial stress different from those that were not?

To answer these questions we have used the following definitions of economic downturns: An episode of financial stress is followed by an economic slowdown if the level of real GDP falls below trend (identified using the Hodrick-Prescott filter for Trend-Cycle

Decompositions) within six quarters of the onset of the financial stress episode(Hodrick and Prescott 1997).

3.2 Hodrick-Prescott filter

Trend-Cycle decompositions are routine in modern macroeconomics. The basic idea is to decompose the economic series of interest (for example the log of GDP) into the sum of a slowly evolving secular trend and a transitory deviation from it, which is classified as *cycle*:

$$x_t = \tau_t + \xi_t$$

$$\text{Observed Series} = \text{Permanent Trend} + \text{Cycle} \quad (4)$$

However, as these constituent parts (trend and cycle) are not readily observed, any decomposition must necessarily be built on a conceptual artifact. Thus, any trending method must start out by somehow arbitrarily defining what shall be counted as *trend* and as *cycle*, before these elements can be estimated from the data.

The most common method used to extract the trend from a time series is the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997). The HP filter extracts the trend τ_t by solving the following standard-penalty program:

$$\min_{\{\tau_t\}} \sum_{t=1}^T (x_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (5)$$

$\min_{\tau_t} \sum_{t=1}^T (x_t - \tau_t)^2$ is the Goodness of Fit

$\lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$ is the Penalty for Roughness

Where the smoothing parameter λ controls the smoothness of the adjusted trend series, $\hat{\tau}_t$, as $\lambda \rightarrow 0$, the trend approximates the actual series, x_t , while as $\lambda \rightarrow \infty$ the trend becomes linear.

While Hodrick and Prescott (1997) suggest values for λ , Marcet and Ravn (2003) recast the formula (5) as a constrained minimization program to determine the value of λ endogenously. For annual data, λ should be between 6 and 7,(Ravn and Uhlig2002;Maravall2004). Note that the HP formula (5) can be written more succinctly as⁴:

$$\min_{\{\tau_t\}} \sum_{t=1}^T \xi_t^2 + \lambda \sum_{t=3}^T (\nabla^2 \tau_t)^2 \quad (6)$$

Which indicates that the HP filter attempts to maximize the fit of the trend to the series (i.e. minimize the cycle component in (4)) while minimizing the changes in the trend's slope.

Based upon these definitions, of the 37 financial stress episodes, 12(8+4) were followed by an economic downturn. The remaining 25 financial stress episodes were not followed by an economic downturn. (Table 2, Figure 3&4). The eight FSI episodes for North Africa countries, South Africa & Turkey followed by an economic downturn correspond to the periods: 2001Q1, 2001Q2, 2001Q3, 2005Q1, 2005Q2, 2008Q4, 2009Q1 and 2009Q2. For the GCC countries, the four periods corresponding to economic downturns are: 2008Q3, 2008Q4, 2009Q1 and 2009Q2. On the whole, all these downturn periods are recorded in the peak periods of the last world financial turmoil, mainly for the GCC countries; the difference for North Africa countries, South Africa and Turkey remain fundamentally characterized by the Turkish financial crisis (2000-2001). Because of the sharp decline in oil prices since mid-2008, GCC countries have experienced a significantly lower economic growth in 2009 than the previous year, with the exception of Qatar.

⁴Where $\nabla = (1 - B)$ is the standard differencing operator and B is the standard backshift (lag) operator, such that $B_{x_t}^j = x_{t-j}$, and $\nabla_{x_t} = x_t - x_{t-1}$. Also define the forward shifting operators: $F = B^{-1}$ and $\Delta = (1 - F)$.

In particular, when preceded by financial stress, economic slowdowns tend to be characterized by a flattening in consumption growth. More detailed conclusions are presented in the discussion section.

4. Markov-Switching Time-Varying Transition Probabilities

We consider a two-state Markov switching autoregressive model for the FSI. Both states, also called regimes, are intended to discriminate between periods of *low financial stress* and *high financial stress*. The regimes are not pre-selected (as would be the case if we were using a 0-1 dummy variable). Instead, we let the model say whether at a given time t the FSI index is considered to evolve in a low financial stress or high financial stress regime, owing to the fact that the likelihood of being in either regime is governed by a latent unobservable two-state Markov chain variable. The formalization below follows Filardo and Gordon (1998), Laton and Smith (2007), Kim *et al.* (2010).

Suppose that y_t is the FSI index observed at time $t = 1, 2, \dots, T$. Its dynamics is given by the following equation:

$$y_t = \mu(s_t) + \phi(s_t)y_{t-1} + \sigma\varepsilon_t\varepsilon_t \sim N(0,1) \quad (7)$$

$s_t = \{0,1\}$ is a latent variable and: $\mu(s_t) = \mu_1 + \mu_2 s_t$, with $\phi(s_t) = \phi_1 + \phi_2 s_t$, $\mu(s_t)$ and $\phi(s_t)$ indicate that the average value of FSI and its autoregressive dynamics is regime-dependent. Equation (7) can be generalized in order to include higher lags and a state-dependent residual standard error.

Since, s_t is assumed to follow a Markov-chain, the realization of each state is assigned a probability and the transition probability matrix is written as follows:

$$P(s_t = i / s_{t-1} = j, L_t) = \begin{bmatrix} p(L_t) & 1 - p(L_t) \\ 1 - q(L_t) & q(L_t) \end{bmatrix}, \quad i, j = 1, 2 \quad (8)$$

Where $L_t = \{L_t, L_{t-1}, \dots\}$ is the history of the leading indicator of the Financial Stress Index (currency and/or banking crisis.). This formalization assumes that a country's currency and/or banking crisis is informative with regard to the likelihood of a higher or a lower financial stress.

The functional form of the functions $p(L)$ and $q(L)$ is assumed to be sigmoid and to map the leading indicator values into the $[0,1]$ interval (logistic, Gaussian, Cauchy distributions). We assume here a logistic function, as is common wisdom in the empirical literature using this class of models:

$$p(L_t) = \frac{\exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})}{1 + \exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})}, \quad q(L_t) = \frac{\exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})}{1 + \exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})} \quad (9)$$

Assume that the two states correspond respectively to a lower financial stress (state 0) and a higher financial stress (state 1). Then, we might have the following situations:

1. $\sum_{m=1}^M \theta_m^p L_{t-m}$ and $\sum_{m=1}^M \theta_m^q L_{t-m}$:
The currency and/or banking crisis is not informative about a forthcoming lower or higher financial stress. The model is a Hamilton (1991) model (if $(L_t \neq 0$ and/or $q(L_t) \neq 0)$) in the sense that the FSI index evolves in two regimes, but there are other variables explaining this. In the case $p(L_t) = q(L_t) = 0$, the dynamics of the FSI index is governed by a linear AR model and is not regime-dependent.
2. $\sum_{m=1}^M \theta_m^p L_{t-m} > 0$ (< 0):
A positive change in the leading indicator increases (resp. reduces) the likelihood of a low financial stress regime m quarters later.
3. $\sum_{m=1}^M \theta_m^q L_{t-m} > 0$ (< 0):

A positive change in the leading indicator increases (resp. reduces) the likelihood of a high financial stress regime m quarters later.

4. $\sum_{m=1}^M \theta_m^p L_{t-m} = 0$ and $\sum_{m=1}^M \theta_m^q L_{t-m} > 0$ (< 0) :

The leading indicator is uninformative regarding the transition dynamics during the shifting from a low financial stress regime to a high financial stress regime. A positive shift in the leading indicator helps predict whether there is an increased or reduced likelihood of observing a high financial stress regime m periods later only when the economy is already in a financial stress regime.

5. Symmetrical situation of case 4 when $\sum_{m=1}^M \theta_m^p L_{t-m} > 0$ (< 0) and $\sum_{m=1}^M \theta_m^q L_{t-m} = 0$: One can predict the likelihood of a lower stress regime only if the economy is already in that regime.

The last two cases illustrates situations in which it may be impossible (using the information contained in the financial variable) to say whether one can expect escape from a financial stress situation or go back to a low financial stress situation. Hence, the transition probability matrix can be presented also as follows:

$$P(s_t = i/s_{t-1} = j, L_t) = \begin{bmatrix} p(L_t) = \frac{\exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})}{1 + \exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})} & 1 - p(L_t) = 1 - \frac{\exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})}{1 + \exp(\theta_0^p + \sum_{m=1}^M \theta_m^p L_{t-m})} \\ 1 - q(L_t) = 1 - \frac{\exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})}{1 + \exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})} & q(L_t) = \frac{\exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})}{1 + \exp(\theta_0^q + \sum_{m=1}^M \theta_m^q L_{t-m})} \end{bmatrix}$$

The parameters of Equations (7) through (9) are estimated jointly using maximum likelihood (ML) estimator for mixtures of Gaussian distributions. As shown by Kiefer (1978), if the errors are normally distributed, then the ML yields consistent and asymptotically efficient estimates. Further, the inverse of the matrix of second partial derivatives of the likelihood function computed at the true parameter values is a consistent estimate of the asymptotic variance-covariance matrix of the parameter values.

As illustrated below, the negative effects of the crises from the advanced economies (mainly the USA and Europe) influenced North African countries, South Africa and Turkey.

Once again, the GCC countries confirm their position as oil exporters with large financial capacity and relatively small populations. This group was in the best position to absorb the economic shocks. They entered the crisis in an exceptionally strong position. This gave them a significant cushion against the initial impact of the global financial crisis. Although their stock markets were hard hit in the second half of 2008, their governments were able to respond by relaxing monetary policy, by providing capital, and by guaranteeing deposits in national financial institutions.

Regarding North Africa countries, South Africa and Turkey, their economies are diversified with strong trade and tourism linkages with Europe and OECD. This group of countries felt the impact of the crisis on their real economy as early as the last quarter of 2008 as recession spread across Europe and other exports markets (Figure 9). For this reason, the impact of the crisis was immediate in comparison with GCC countries.

5. Self-Organizing and Cost-Sensitive Learning Vector Quantization Networks Methodology

Self-organizing in networks is one of the most fascinating topics in the neural network field. Such networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. Self-organizing maps (SOM) learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors.

Learning vector quantization (LVQ) is a method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors.

However, the classes that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer probably will put them in the same class. There is no mechanism in a strictly competitive layer design to say whether or not any two input vectors are in the same class or different classes.

LVQ networks, on the other hand, learn to classify input vectors into target classes chosen by the user (Kohonen, 1987).

The cost-sensitive LVQ resembles the basic batch LVQ except that the misclassification costs are utilized as weights guiding the prototype learning so that more attention is paid to the class associated with higher cost. During the training process, an input vector x is projected to the best-matching unit (BMU), i.e., the winner with the closest prototype according to the distance measurement d .

$$BMU(x) = \operatorname{argmin}_{1 \leq i \leq m} d(x, m_i) \quad (1)$$

The projection of input x_i (is $1 \leq i \leq m$) is defined by an indicative function h_{ip} whose value is 1 if m_p is the BMU of x_i , and 0 otherwise:

$$h_{ip} = \begin{cases} 1 & \text{if } m_p = BMU(x_i) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Regarding the BMU, a Voronoi set V_i is generated for each neuron and composed of the observations projected to the neuron. In the Voronoi set, an element is positive if its class label agrees with the map neuron, and negative otherwise. Positive examples move the prototype towards the input while negative examples move the prototype away from them. Intuitively, the positive examples of relatively higher cost should impose more impact on the prototypes so that they are harder to be misclassified. The denotative function s_{ip} takes $C_{label(x_i)}$, which is the misclassification cost associated with the class of observation x_i , as the value in case of positive example, and -1 otherwise.

$$s_{ip} = \begin{cases} C_{label(x_i)} & \text{if } label(m_p) = label(x_i) \\ -1 & \text{otherwise} \end{cases} \quad (3)$$

The indicative and denotative functions are then used in the prototype update, which combines the contribution of positive examples and suppression of negative examples to each neuron in a batch round. Let $m_p(t)$ be the prototype vector of the p^{th} unit at epoch t . The update rule of cost-sensitive LVQ is formulated as follows (If the denominator is 0 or negative for some m_p , no updating is done):

$$m_p(t+1) = \frac{\sum_{i=1}^n h_i s_{ip} x_i}{\sum_{i=1}^n h_i s_{ip}} \quad (4)$$

As a special case of SOM, the LVQ algorithms benefit from a trained map by a preceding SOM in the initialization (Kohonen 1987). In one round, one instance x_i is input and the distance between x_i and prototypes is calculated, consequently the input is projected to the BMU according to Equation (1). After all the inputs are processed, the neurons are assigned by the majority of class labels in Voronoi set for acquiring the labeled map. In other words, if there are more good examples than bad examples, the unit is labeled as good and conversely. Then the values of indicative and denotative functions are calculated for each pair of input and neuron regarding Equation (2) and (3). Afterwards, the prototypes are updated according to Equation (4). This training process is repeated iteratively until the maximum number of iteration is reached or the amount of variation of prototypes between two consecutive iterations is less than a specified threshold. In summary, the algorithm is performed as follows:

1. For $p = 1, \dots, m$, initialize the map with prototypes m_p ;

2. For $i = 1, \dots, n$, input instance x_i to the map and project it to the BMU;
3. For $p = 1, \dots, m$, assign the class $\text{tomp}(t)$ by majority labeling principle;
4. For $i = 1, \dots, n, p = 1, \dots, m$, calculate hip and sip ;
5. For $p = 1, \dots, m$, calculate the new prototype $\text{pemp}(t + 1)$ for the next epoch;
6. Repeat from Step 2 a few iterations until the termination condition is satisfied.

5.1 Data sets and empirical simulations

The proposed cost-sensitive LVQ algorithms are implemented based on some toolbox (Stork, Elad 2003) in Matlab. We mainly concern about the effectiveness of the proposed algorithms on the tradeoff between two kinds of errors and the improvement on the total misclassification error rather than on the comparison with competing classification models.

Concerning the data set, the capability of cost-sensitive LVQ is validated by a data set representing most important information for an economic system from January 2000 to December 2010 (11 years). In order to diversify the number of examples in the data set, a Monte Carlo simulation is conducted to create weekly data. After simulation, the data set contains 528 examples. 8 years are used as the learning data set and 3 years as a testing and prediction set. The learning data set contain 272 bad examples and 256 good examples. The decision about good or bad examples is referenced to the variables thresholds according to the largest economy in the selected region, (South Africa for NA-SA-T countries and UEA for GCC countries). As described in Table 3, each country is characterized by a set of 27 variables besides the independent class. The problem is to predict whether a country is under a situation of economic slowdown over a given period (one year).

The variables values are transformed with a logarithm calculation. The new values are then normalized in order to transform the maximum and the minimum value to 1 and 0 respectively.

$$y = \begin{cases} \log(x + 1) & \text{if } x > 0 \\ -\log(1 - x) & \text{otherwise} \end{cases} \quad (5)$$

$$y = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (6)$$

5.2 Evaluation criteria of the cost-sensitive learning vector

In the real life, the classification problems are commonly encountered. In general, most classifiers assume that the misclassification costs (false/bad and false/good cost) are the same. This assumption is not true. For example, in customer relationship management, the cost of mailing to non-buyers is less than the cost of not mailing to the buyers (Elkan2001). In this case, cost is not necessarily monetary, for examples, it can be a waste of time.

G_b denotes a misclassified good example, and a misclassified bad example is denoted by B_g . C_i, j is the cost of predicting an example belonging to class i when in fact it belongs to class j . The cost matrix or the confusion matrix is defined as follow:

All the examples in the data set can be classified into class i . Mathematically, we can define the (i, j) entry in the cost matrix C the cost of predicting class i when the true class is j . If $i = j$, then the prediction is correct. Otherwise, the prediction is wrong. The optimal prediction for an example x is the class i with the minimum expected cost by using the Bayes risk criterion (Chen, Marques, 2009):

$$L(x, i) = \arg \min_i \left(\sum_{j \in \{b, g\}} P(j|x) \cdot C(i, j) \right) \quad (7)$$

where $P(j, x)$ is the posterior probability of classifying an example x as class j . We assume that there is no cost for correct classifications, so the cost matrix can be described by the cost ratio:

$$CR = \frac{C_{Gb}}{C_{Bg}} \quad (8)$$

The purpose of Cost-Sensitive Learning is to build a model with minimum misclassification costs (total cost):

$$T.C = (C_{Gb}).FB + (C_{Bg}).FG \quad (9)$$

Where: FB and FG are the number of false bad and false good examples respectively.

The most used assessment criteria for the predictive capability are:

- Type I error rate (fraction of good examples classified wrongly to bad classes): Gb/G
- Type II error rate (fraction of bad examples classified wrongly to good classes): Bg/B
- Overall error rate (percent of examples classified incorrectly): $(Gb+Bg)/\text{Total examples}$. The overall error treats two kinds of errors, namely type I error and type II error equivalently. Accordingly, the complementary rates denote the percent of observations classified correctly.

5.3 Experimental results

The experiments are performed in the following steps:

1. The entire data set is divided randomly into 11 folds for cross-validation, in which 8 folds are used for model training, and the remaining is used for testing the generalization capability of the built model.
2. In each trial, the cost-sensitive LVQ algorithm is applied to the training data set.
3. For validation, each sample of the data test is set as an input to the resultant map and the predicted class is the label of the BMU.
4. After the experiment is repeated 10 times, the confusion matrix is calculated by comparing the real class to the predicted class for the entire data. Then the evaluation criteria are obtained from the confusion matrix.

The simulations produced 16 major classifications. The corresponding confusion matrix is summarized in Table 5. It can be concluded that the cost-sensitive LVQ is able to improve the predictive capability on the class with higher cost without great degradation on the other class. Since the misclassification cost on *bad* category is higher, the classifier achieving lower type II error is preferred in practice.

The performance tendency can be detected in Figure 10, in which the left graph shows the error rates with respect to the varying cost ratios, and the right graph shows the cost ratio evolution.

It is observed that the cost-sensitive learning is a good solution to the class imbalance problem by assigning different costs to different classes. Hence the proposed algorithm can be employed for distress signals prediction.

In a second stage of simulations, we have established a neural network for detecting early warning signals (a financial crisis) in an economic system. Traditionally, the performance assessment of a warning tool is based on two measures, which can be defined from the following matrix:

Let A represents the number of true signals released when a crisis is indeed taking place and B is the number of false or noise signals when no crisis is on stake. C is the number of false silences (no-signal) and D is the number of true silences. The table indicates if a signal (or a no-signal) occurs during one year (or 12 months).

We begin by assessing the quality of our system; we thus calculate conditional probabilities based upon the cell counts in the contingency table. We calculate the percentage of time over which the indicator released a signal when there was a crisis. In this case we are looking only at the *crisis* column of the contingency table to compute the probability that a signal was released. This probability is given by $A/(A + C)$. A high probability is associated with a good quality of the model. We also need to know how noisy the signal is. In particular, if no crisis occurs over the forecast horizon, we have to determine how often the indicator released a signal. Looking at the *no crisis* column of the contingency table, the ratio $B/(B + D)$ is calculated. A lower probability is a signal of a good model.

Let the noise-to-signal ratio represent a measure of the background noise relative to the signal strength. The ratio is usually measured by the following equation:

$$NSR = \frac{B/(B+D)}{A/(A+C)} \quad (10)$$

The smaller the NSR is, the better the indicator is for signaling a financial crisis. Table 7 presents the performance results:

The performance obtained using neural networks is good for our forecasting horizon since the NSR approaches zero. This very small NSR is associated with significant coverage, i.e. 100% of distress signals. This implies that the proposed learning approach is a very promising.

Also, the most important crises in the considered period (from January 2000 to March 2010) are successfully captured, 136 distress signals for North Africa, South Africa & Turkey identified as follow: 2001Q1, 2001Q2, 2001Q3, 2005Q1, 2005Q2, 2008Q4, 2009Q1 and 2009Q2 (128 weeks) plus 2010's two last month (8 weeks) representing the Turkish financial crisis beginning. 67 distress signals for GCC countries identified as follow: 2008Q3, 2008Q4, 2009Q1 and 2009Q2 (64 weeks), the three remaining weeks are considered as misclassified examples in the data set. However, the model also released 4 false signals while there was no distress (2 signals for North Africa, South Africa & Turkey and 2 signals for GCC countries).

It can be concluded that the proposed approaches performs well. The main reason is that the Self-organizing neural networks (based-on cost sensitive learning vector analysis) produce some intrinsic functions with different scales, which simplifies the problem. Furthermore, different functions with different scales include different information and, therefore, the neural network is able to extract more knowledge, thereby increasing its generalization ability. However, the main drawback of the Self-organizing neural network can be covered by the Markov-switching time-varying transition model for identifying more clearly episodes of financial stress followed or not by an economic downturn.

6. Conclusions and Policy Implications

Early warning signals in economic systems have been considered as an important topic in many economic domains to evaluate the risk associated in decisions concerning a state or a nation. Due to the presence of unequal misclassification costs in practical applications, the cost-sensitive classification is of particular importance to distress prediction. The previous sections have shown that only about third of the episodes of financial stress identified in this paper were followed by economic slowdown. So, we could say that not all financial stress episodes are going to be likely followed by economic downturns, only the most episodes with high FSI can lead to severe and prolonged of these downturns.

An analysis of the episodes suggests that banking system stress tends to be associated with larger output consequences than episodes of pure securities or foreign exchange market stresses, where the banking system remains largely unaffected. Around 75 percent of the episodes of financial stress are banking-related. Moreover all severe economic downturns are

preceded by a high banking-related financial stress episodes compared with other types of financial stress episodes. In fact, the difference between banking-related and non-banking-related episodes is significant. Consequently, downturns preceded by banking related stress tend to last longer, and are associated with larger average GDP losses, than those preceded by different types of financial stress, or indeed no financial stress at all.

Also, the analysis explains some spillover effects and reveals that crises are transmitted mainly from advanced economies to emerging economies. In line with this pattern, the unprecedented spike in financial stress in advanced economies in the third quarter of 2008 had a major effect on emerging economies.

Using the FSI, this paper has empirically investigated how macro-financial vulnerabilities produce economic downturns in some MENA countries. In addition, results show that the considered North Africa countries, South Africa and Turkey were less robust and more influenced in comparison with GCC countries in episodes of financial stress and downturns in economic activity in advanced economies.

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Figure 1 : Financial Stress in NA-SA-T Countries

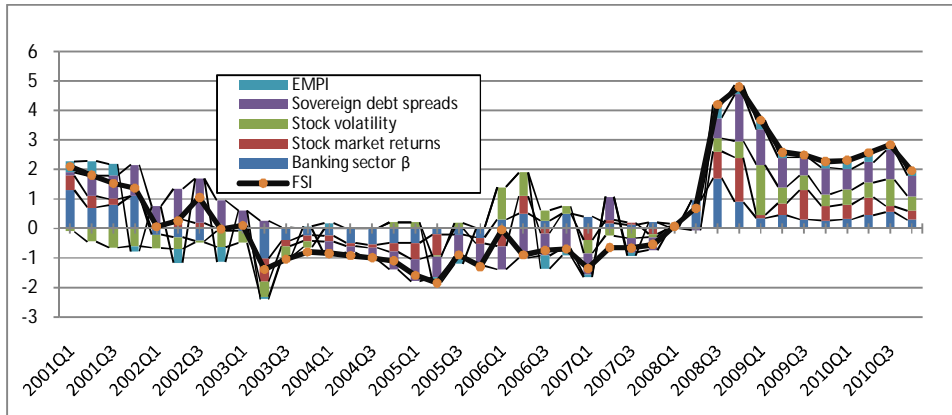
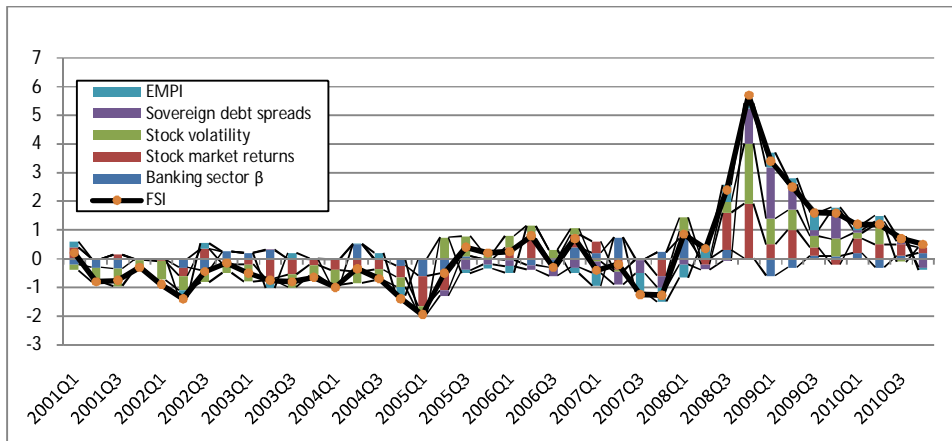
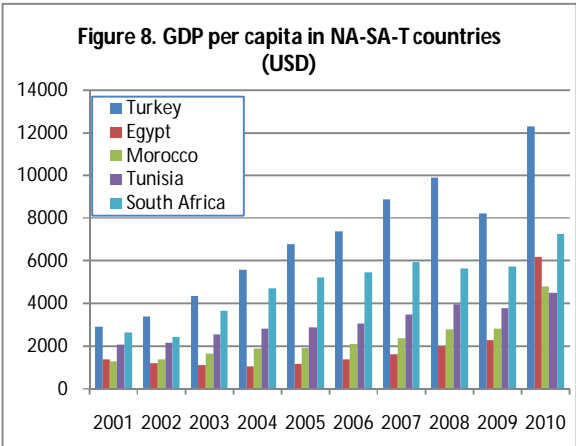
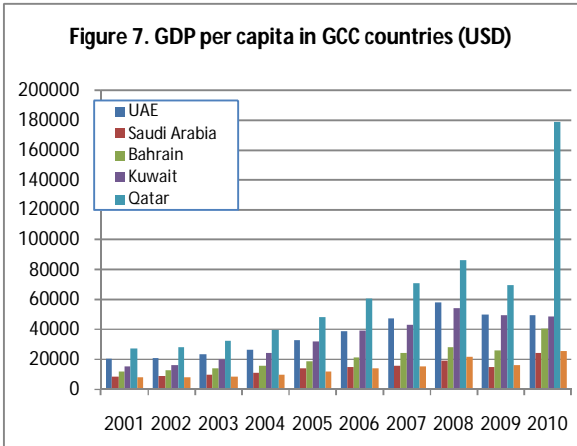
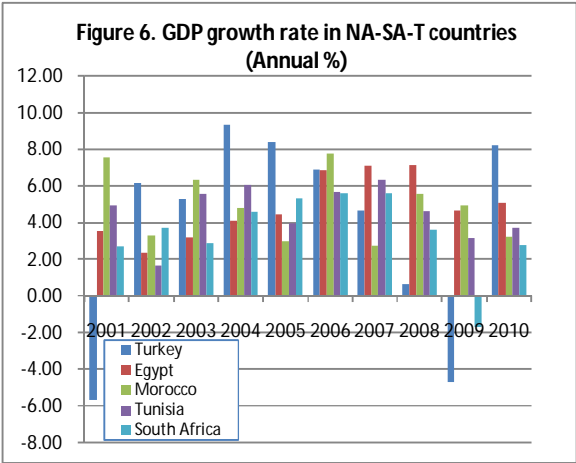
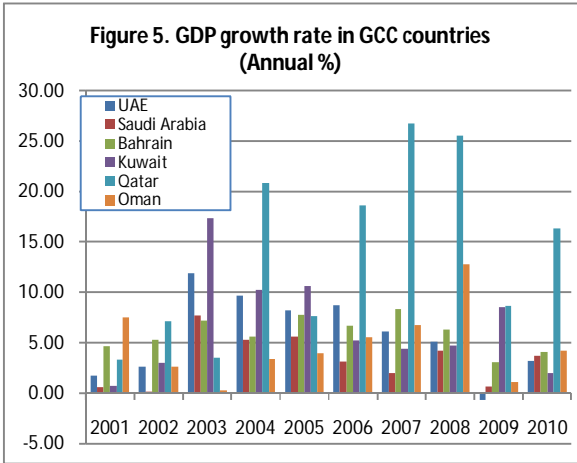
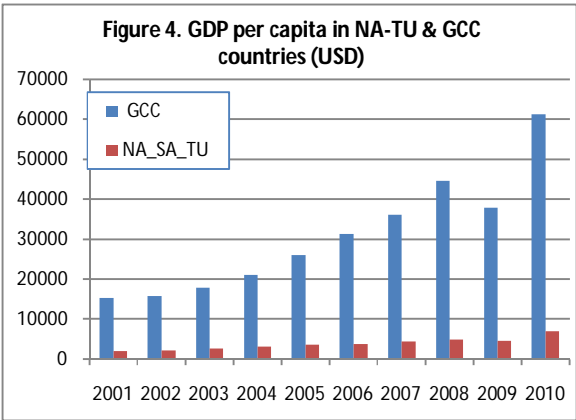
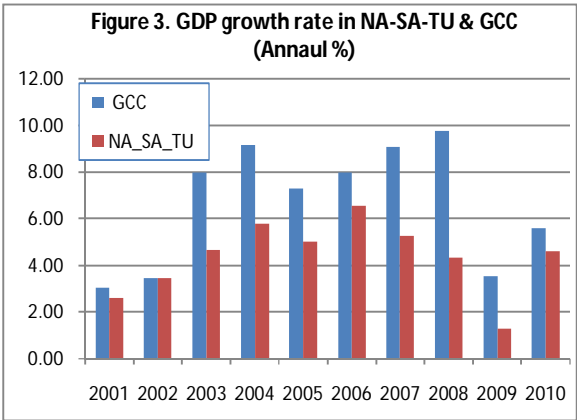


Figure 2: Financial Stress in GCC countries





Source: World Bank, OCED statistics& CIA World Factbook.

Figure 9 : Markov-Switching Time Varying Transition Probability for EM_FSI to NA-SA-T_FSI and GCC_FSI

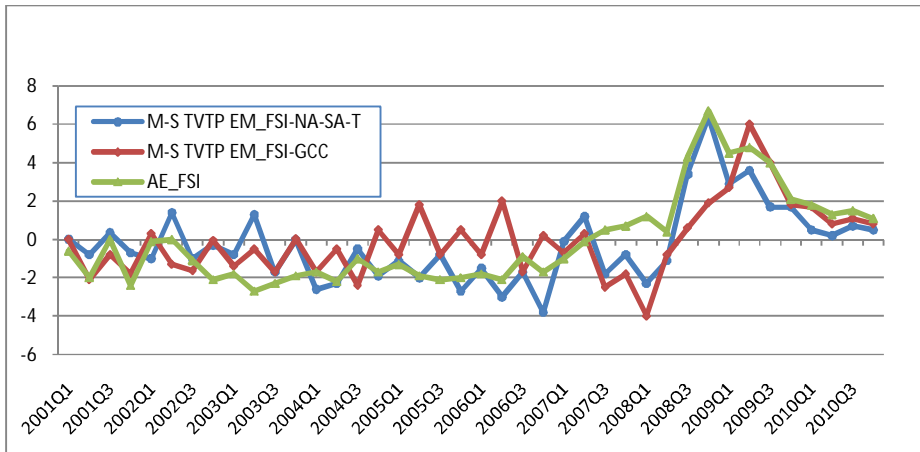


Figure 10: Simulation Results

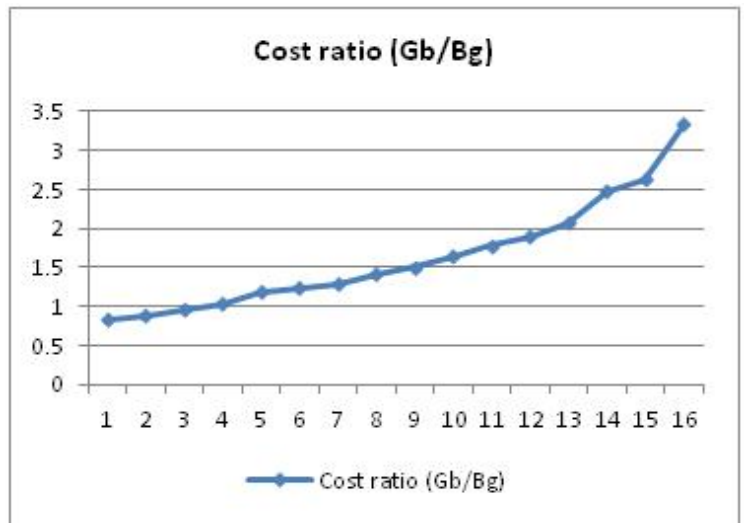
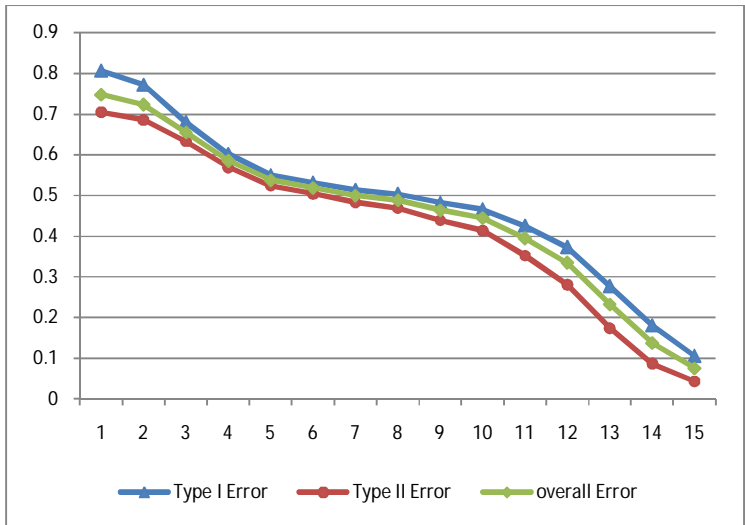


Table 1: Financial Stress Episodes

	North Africa countries, South Africa and Turkey	Gulf Cooperation Council countries	Total
Banking crisis	18	10	28
Foreign exchange	5	4	9
High FSI	15	7	22
Low FSI	8	7	15
Total Financial Stress Episodes	23	14	37

Table 2: Financial Stress Episodes and Economic Downturns*

	North Africa countries, South Africa and Turkey	Gulf Cooperation Council countries	Total
FSI followed by economic downturn	8	4	12
FSI not-followed by economic downturn	15	10	25
Total Financial Stress Episodes	23	14	37

Notes: *Downturn: number of quarters where GDP is below the Hodrick-Prescott trend

Table 3: Neural Network Input and Output Variables

X _i	Variable description	X _i	Variable description	X _i	Variable description
X1	Annual real GDP growth	X10	Current account balance (USD million)	X19	Inward FDI Potential Index
X2	Demand Composition and growth rate	X11	Current account balance (as % of GDP)	X20	ODA net total, All donors
X3	Total revenue and grants	X12	Exports	X21	ODA net total, DAC countries
X4	Total expenditure and net lending	X13	Diversification index	X22	ODA net total, Multilateral
X5	Inflation	X14	Annual export growth	X23	Debt outstanding, at year end
X6	Exchange Rate	X15	Competitiveness Indicator	X24	Total debt outstanding (as % of GDP)
X7	Broad Money	X16	Foreign Direct Investment inflows	X25	Debt service (as % of Exports of goods and services)
X8	Reserves	X17	Foreign Direct Investment outflows	X26	Telecommunications
X9	Trade balance (USD million)	X18	FDI inflows/GFCF	X27	Unemployment rate
				X28	Class (Healthy, distress)

Table 4: Cost (confusion) Matrix

Actual class	Predicted class		Total
	Bad	Good	
Bad	Bb	Bg	B
Good	Gb	Gg	G
Total	b	g	T

Table 5: Cost matrix

		Predicted class																		
		GCC countries				North Africa, South Africa & Turkey				North Africa, South Africa & Turkey				North Africa, South Africa & Turkey						
		Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error			
Real class	Bad	89	212	301	0.806167401	93	203	296	0.7715517	102	176	278	0.68	115	152	267	0.6015326			
	Good	183	44	227	0.704318937	179	53	232	0.6858108	170	80	250	0.6330935	157	104	261	0.5692884			
	Total	272	256	528	0.7481061	272	256	528	0.72348	272	256	528	0.6553	272	256	528	0.58523			
	Cost matrix				0.863207547					0.8817734					0.969091					1.0328947
			Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error		
	Bad	118	130	248	0.55	120	122	242	0.5314685	123	115	238	0.5137931	121	107	228	0.5033333			
	Good	154	126	280	0.524193548	152	134	286	0.5041322	149	141	290	0.4831933	151	149	300	0.4692982			
	Total	272	256	528	0.5378788	272	256	528	0.51894	272	256	528	0.5	272	256	528	0.48864			
	Cost matrix				1.184615385					1.2459016					1.2956522					1.411215
			Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error		
	Bad	125	98	223	0.481967213	126	89	215	0.4664537	138	75	213	0.4253968	156	61	217	0.3729904			
	Good	147	158	305	0.439461883	146	167	313	0.4139535	134	181	315	0.3521127	116	195	311	0.281106			
	Total	272	256	528	0.4640152	272	256	528	0.44508	272	256	528	0.39583	272	256	528	0.33523			
	Cost matrix				1.5					1.6404494					1.7866667					1.9016393
			Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error	Bad	Good	Total	Type III/overall error		
	Bad	189	40	229	0.277591973	220	21	241	0.1811847	243	11	254	0.1088394	262	3	265	0.0380228			
Good	83	216	299	0.174672489	52	235	287	0.0871369	29	245	274	0.0433071	10	253	263	0.0113208				
Total	272	256	528	0.2329545	272	256	528	0.13826	272	256	528	0.07576	272	256	528	0.02462				
Cost matrix				2.075					2.4761905					2.6363636					3.3333333	

Table 6: Contingency Table

	Distress	Healthy
Signal	A	B
No Signal	C	D

Table 7: Classification Results

		GCC countries			North Africa, South Africa & Turkey				
		Predicted class			Predicted class				
		Distress	Healthy	Total		Distress	Healthy	Total	
Real class	Signal	67	2	69	Real class	Signal	136	2	140
	Non signal	0	459	459		Non signal	0	388	388
	Total	67	461	528		Total	136	392	528
	A/A+C	100%	---			A/A+C	100%	---	
	B/B+D	---	0,43%			B/B+D	---	0,51%	
	NSR	0,00433				NSR	0,00510		