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A Fuzzy Based Early Warning System to Predict Banking Distress on Selected Asia-Pacific Countries*

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Abstract

This study develops an early warning system (EWS) to prevent the banking crisis. The proposed system incorporates both the perspective of crises and fundamental characteristics of the banking system in each economy. A fuzzy logic method with data from 1990-2009 is employed to construct the EWS of banking crisis based on 21 pre-determined variables from the aspect of total economy, financial and banking sectors. Our results show: Firstly, South Korea recorded higher probability to have a banking crisis in 1997 as there was large foreign debt in dollars. Secondly, China, Australia and New Zealand banking systems appear to be vulnerable to the crisis in 2007. The surge of China export, FDIs and booming stock market were signs of a heated economy. Australia with high commodity prices was also vulnerable to crisis. Thirdly, Australia, China, Japan and New Zealand banking systems appear to be exposed to the higher chance of a crisis in 2010. Japan with deflation coupled with expensive yen did not augur well for its export. Overall, the findings show that in Asian Financial Crisis 1997/98 and Global Financial Crisis 2008/09, many economies are exposed to a higher probability of having the crisis and this shows an urgent need of having surveillance in these economies.

Keywords: Early Warning System, Financial Crisis, Banking Crisis, Fuzzy.

JEL Classification Code: C53, G01, G21, G32, H12.

1. Introduction

In the 1990s, a financial crisis was considered as an event that may occur in an individual economy but the crisis like Asian Financial Crisis (AFC) 1997-98 showed that it could affect the whole economies which have a relationship with the affected economies. The AFC which started from Thailand spread to other neighboring countries like Indonesia, Malaysia, South Korea and Hong Kong within a short span of time. One of the reasons behind in most studies is the unproductive investments guaranteed by the government. Indeed, this huge amount of investment in mega projects and the mismatch of long-term project with short-term financial instruments are the underlying causes which trigger the start of a crisis. At the same time, the activities of protecting depositors and financial institutions have caused governments to accumulate a huge amount of contingent liabilities. In addition, inter-economies trading activities also allow the crisis to permeate to other economies.

The other source of the crisis was the weak financial markets at the international level. At first, it was not imaginable that whole region was bound to such crisis, but when the panic started in Thailand, investors pushed it to the rest of the region. In fact, the investors' re-evaluations of risks related to Malaysia, Indonesia and South Korea led to a huge outflow of funds from these countries. Investors' pessimistic expectation and their cautious outlook for the region, and agents' knee-jerk reaction and judgment towards the market movements created a contagion in the Asia Pacific region.

However, according to Filardo et al. (2010), the region has improved to regain stability as the result of all effort to reform the institutions. Efforts by policy makers have stopped the sharp capital outflows, fallen GDP, and disruption in stock exchanges. In contrast, for the

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2007-8 Global Financial Crises (GFC) in Asia, the financial and economic infrastructures were completely sound before the crisis occurred. The published data showed that before the crisis, the region had a healthy banking system, bond markets, and sound fiscal policies.

For the banking system, capital adequacy was more than 10 percent and non-performing loans was reported to be low and even reducing for the region. For the mentioned period, loan to deposit ratio is less than 10 percent in the Asia-Pacific region which means they were independent of wholesale funding. Similarly, development in payment system benefited the microstructure of financial market. Increasing market liquidity, stable inflation (less than 6% for the whole region's economies), healthy fiscal policies and relatively stable economic growth were some of the significant development of the regional economies. In addition, budget surpluses were reported in Thailand, Singapore, New Zealand, Korea, Hong Kong, China and Australia in 2007.

In spite of financial soundness in the region, Asia-Pacific economies were not immune from the crisis and the whole region experienced huge instabilities in their economies as well as the banking system. As a result, a comparison between the 2007-8 crisis and East Asian crisis, shows that both of them rose from booms in asset prices which were due to capital inflows. Also, in both crises, the disaster in the real sectors of the economy started once the asset bubble burst, and the effect was transmitted to the banking system due to increase in non-performing loans, and later to the equity market as pessimistic outlook and poor business sentiment led to capital outflows.

As discussed, the crises imposed crucial costs to the economy. Capital outflows and fall in major macroeconomic variables like GDP, consumption, exports and imports impose direct and indirect costs of the economy. As the result, in the aftermath of crises, the credit crunch in the financial system and credit rationing, further exacerbated the crisis. These huge costs highlight the important role of EWS in the prediction of banking crises. Effective EWS can recognize hidden bank runs and the related risks and suggest policies to prevent potential crises or limit the after effects. On one hand, the role of the banking sector in economic development cannot be neglected, however, excessive lending create speculative activities which build asset bubbles, and subsequently trigger crises which can result in serious disruptions of economic activities (Hoggarth, Reis, & Saporta, 2001). So developing and utilizing effective early warning systems would provide the policy makers with tools to deal with the current crisis as well as prevent future crises.

Specifically, the main objective of this paper is to develop an early warning preventing tool for banking crisis identification. The proposed EWS incorporates a comprehensive perspective of the crises as well as the fundamental characteristics of the banking system for each economy in the studied cases. Also, this research will lead to quantifying the probability of the crisis that relies on a huge variety of the variables. So, in the process of gathering a huge collection of variables in the three most important levels in the economy (total economy, financial sector, and banking sector), this research suggests a richer approach to:

- Design an early warning system to model the systemic banking crises using a fuzzy method.
- Determine the possibility of the occurrence of crisis by transferring a qualitative concept to a quantitative calculation.

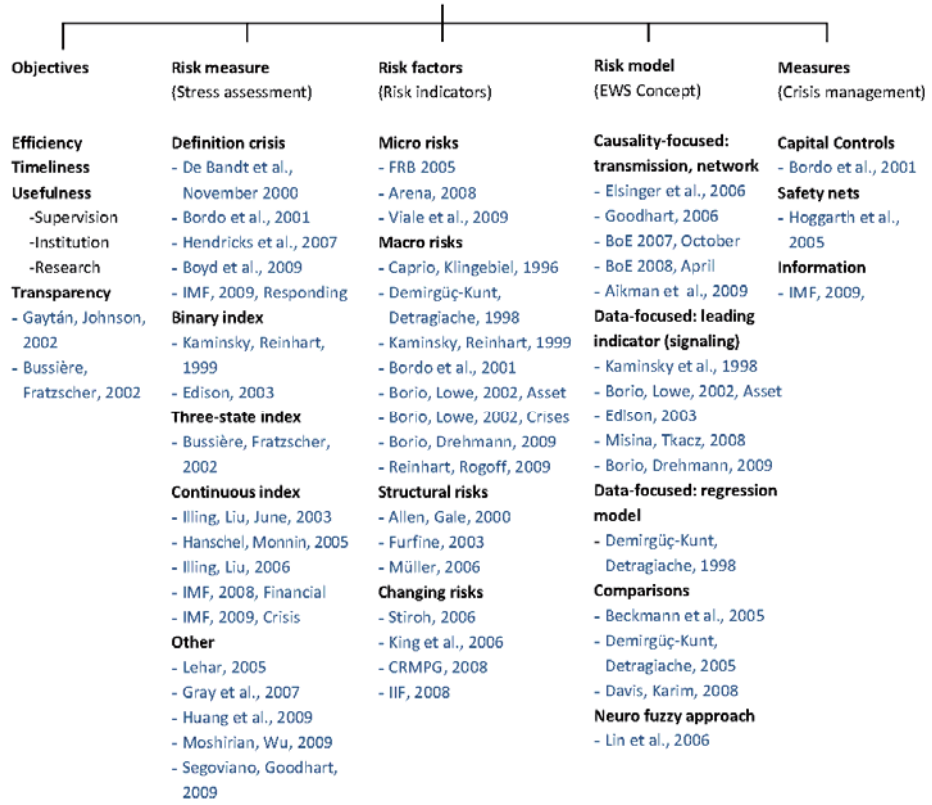
In this study, we consider the Asia Pacific region as our basic case study. The data set includes the emerging and developed economies in the region such as Australia, China, Japan, South Korea, Malaysia, New Zealand and Singapore. In order to analyze the crisis, an index of a crisis in defined according to 21 variables in three levels, total economy, financial sector and the banking sector. The period of time series is the years 1990-2009. Specializing numerical values to economical-critical situations, this study introduces a robust approach to prove the possibility of the crisis in different levels of the economy without engaging in the complicated direct and indirect relationships among them. Utilizing a fuzzy approach this study developed an early warning system that can recognize the crisis and determine its power, according to the historical changes of the variables.

2. Literature Review

Totally, the literature on EWSs in banking categorize the major elements of any EWS as below:

- Definition and quantification of the distress
- Models and methodologies
- Distress variables

Combining these three major elements develops different designs of EWSs. The most efficient of these possible systems is chosen according to main objectives and the needs of any user (Davis & Karim, 2008; Gaytán & Johnson, 2002). Figure 1 shows the main elements of EWSs mentioned by different researchers in recent decades.



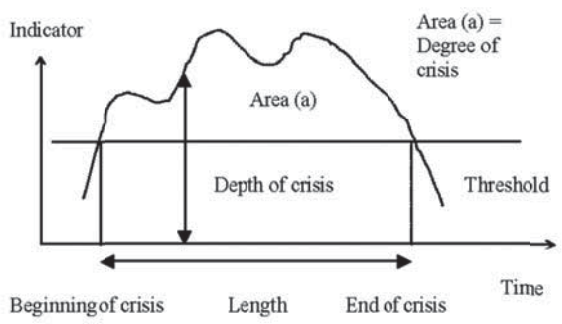
Source: Gramlich, Miller, Oet, & Ong (2010)

<Figure 1> Main Elements of EWSs

Actually, there is no pre-determined or conceptual definition of the financial crisis before the 1990s. According to Aziz, Caramazza, and Salgado (2000) and Ishihara (2005), financial crisis consists of three main categories: banking, currency and foreign debt crisis. In these studies, financial market inefficiency introduced as the main reason for the crisis that transmits disruptions to the real part of the economy through the banking system. The definition of distress in the banking system is the subject of a lot of prediction models and basically, it can be said the first step in designing such model is to quantify the distress. The output of this process is a particular definition of the crisis that will lead to a particular forecast at a particular time.

According to recorded data on the banking crisis, this kind of crisis origins in two concepts; liquidity and insolvency. Normally, the ratio of demand deposit and capital to a number of assets usually figure out these kinds of crises. In fact, liquidity crisis turns up when a bank cannot meet its creditor obligations and solvency crisis situates when the liabilities grows more than assets. In several types of research, the instability, financial indices related to assets, liabilities, NLPs and capital are examined to identify this form of crisis. Also, employing some policies by government, such as nationalization or recapitalizing of banks and contractionary policies may be a signal of the crisis in a way (Ishihara, 2005). Additionally, distortion in local currency which associated banking crisis to the currency crisis that is called ‘twin crises'.

Indeed, sudden variations in some macroeconomic variables such as liquidity, credit, interest rates, assets, and liabilities can be treated as the signals of a crisis in the banking system. According to Ishihara (2005), simply, the approach to identify a crisis can be introducing an indicator and compare it with an appropriate threshold. Overpassing the indicator of the amount of threshold is a signal of crisis and the gap between these two amounts is the degree of crisis. (Figure 2)



Source: Ishihara (2005)

<Figure 2> Simple Approach to Identify the Crisis

In fact, the role of modeling in an EWS is to connect the distress indicators and the predictions. In modeling a distress, we are seeking for a rule to link the signals of the market to an effective anticipation and the result of this process is a framework that determines our EWS. Considering 150 papers in the field of early warning methodology, Yucel (2011) shows that the period 2001 up to 2005 is the pick of researchers about early warning models in the world. Also, he introduced the year of 1996 as the starting point of this jump result of globalization. Amongst the models are implied in this period, logit analysis, signal extraction and factor analysis were the most utilized methodologies and fiscal balance, the balance of payments, monetary aggregates, credits, exchange and interest rates and domestic economic indicators are the most employed variables in these studies (Table 1 and Table 2).

<Table 1> The Most Popular Models Used in EWSs

ARMA	2	
Forecasts&combinations	4	
Regression (p/np)	8	
VAR&simultaneous equations	2	
VARMA-GARCH	1	17
Burrit	1	
Linear probability model	1	
Logit	21	
Lomit	1	
Probit	7	31
Analytical hierarchy process	1	
Binary recursive tree	1	
Clustering	2	
Diffusion index	2	
Discriminant analysis	12	
Factor analysis	2	
Lachenbruch classification	1	
Survival analysis	1	
Trait recognition analysis	1	23
Signal extraction	14	
Signal extraction (real time)	1	15
Artificial Neural Networks	2	2
Exchange market pressure index	4	
Indicators&indices	6	10
Markov-switching	6	6
Bayesian belief revision	1	1
Simulation	1	
Value-at-Risk	2	3
CAAMPL	1	
CAMEL	2	
Catastrophe	1	
Damocles (Lehman Brothers)	1	
Descriptive	3	
Expert opinion&qualitative	2	
Gini's transvariation	1	
Hill-1975 tail index	1	
MIMIC	1	
Ratio analysis	1	
Survey	1	
Topological analysis	1	16
Total		124

Source: Yucel (2011)

<Table 2> The Most Popular Variables Used in EWSs

M1,M2,M3 (excess balances)	8	
M1,M2,M3 (multipliers)	11	
M1,M2,M3 (other ratios)	14	
M1,M2,M3, money	15	
M1,M2,M3/Reserves	26	74
Bank deposits	11	
Bid-Ask spread	4	
CB credits	8	
Credit&credit growth	9	
Domestic credit	33	
Household debt	1	
Loan volume volatility	5	
Loans&loan growth	5	76
Average maturity&duration	9	
Capital adequacy	5	
Non-Performing Loans	13	27
Capacity utilization	1	
GDP&growth&composition	44	
Indicators	6	
IP&economic activity	12	
Stock market&prices	31	
Unemployment	1	95
World growth&performance	4	
World&DC interest rates	8	12

Fiscal balance	24	24
Capital account	5	
Current account	16	
Exports&Imports	46	
Debt&debt service	9	
External debt	19	
FDI&Portfolio	8	
FX reserves	26	129
Exchange rates	11	
Interest rate repricing period	4	
Interest rates&differentials	15	
Real Exchange Rates	27	
Real Interest Rates	24	
Terms of trade	17	98
Expectations	5	
Inflation	27	32
Political&Institutional&Social&Geographical	42	42
Return on Assets&Return on Equity	9	
Value at Risk	3	
Working capital	2	14
Financial ratios&other	382	382
Total		1005

Source: Yucel (2011)

As it can be seen in the above tables, the early warning models used in banking can be grouped into a few major categories: signal extraction models, binary variables models, supervisory models, statistical models and artificial neural networks. Early warning explanatory variables are based on a theory of what causes risk. Since the 1980s, literature on EWSs consists of a transformation in explanatory variables of systemic distress.

In addition, the literature shows there is a complete evolution of the theories about the origins of systemic distress. In the present study, it is shown that factors like macroeconomic deterioration, diverging developments, financial system shocks, banks' idiosyncratic risks, and contagion among institutions in the real economic and financial sectors can lead to financial system's exposure (Illing & Ying, 2003).

In other studies, implying the concept of deviating macroeconomic and financial variables, a design of gap indicator series is presented. The gaps are calculated as deviations of variables from their means, so they are the signs of pressures in the system. In terms of computation, gaps avoid the problems associated with calculating risk factors on an absolute basis. The earlier works view the credit/GDP gap as a fundamental mismatch between economic variables. In the later works, several factors are added, such as commodity prices and international factors but not incorporated due to data limitations. Hanschel and Monnin (2005) are one of these cases that utilize this method.

The crisis of 2007-08 shows there is a need to develop the EWSs. From the consequences of recent turmoil, it is obvious that the common indices of distress such as capital asset ratios and NPLs do not present a complete perspective of the environment in which the bank is acting. Furthermore, an updated EWS needs to integrate several dimensions of the distress.

3. Materials and Methods

After the banking crises in the 1990s, several attempts have been devoted to the structure of a EWS for estimating the probability of the next crisis with the intention of avoiding its recurrence. Different crisis in the world tells us it is needed to prevent or at least a managing function such damage to the world economy, discovering an efficient early warning solution and method that has been turned out an important issue. Nowadays, expert systems have risen suddenly such as Fuzzy Logic and Neural Network of which have been manipulated for providing assistance managers

in generating real-world decision making. The expert system provides the facility of embedding the past experiences into the object system; fuzzy logic makes it possible to describe the problem how it is as close as possible to the process of human reasoning accompanying accommodating the uncertainty and inaccuracy entangled with the data.

Although there are difficulties coming up with the data acquisition of the knowledge base for both fuzzy logic and expert systems and the difficulties with the conventional illustration over the appropriate structure of the “real” relation among the Neural Network model variables which inhibited the implementation of the conventional models (Lin, Khan, Chang, & Wang, 2008). In 1965, this strategy was first proposed by the Zadeh complicated systems control that is too hard to be analyzed by traditional mathematics. But the fuzzy logic theory did not find wide popularity in various applications such as economics, management, medicine, or process control until the 1970’s (Zadeh, Klir, & Yuan, 1996).

Mamdani and Assilian (1975) introduce the first application of fuzzy set theory for controlling a small laboratory steam engine. After the success of this theory, many scientists were inspired to attempt to implement the fuzzy logic, not only in engineering applications but also in other disciplines of science, particularly in Economics. As an example, Alam, et al.(2000) illustrates the fuzzy clustering provides proper classification tools for estimating possibly failing banks. The coefficients of me possible that are developed by the fuzzy clustering algorithm are probabilities of membership group in the Zadeh sense (Kandel, 1982).

Perceptive organs help human brain interprets imprecise and incomplete sensory information. Similarly, fuzzy set theory tries to provide a systematic calculus to deal with such information linguistically, and performs numerical computation by using linguistic labels stipulated by membership functions. To model human expertise in any area, the fuzzy inference system (F.I.S.) should be designed properly (Zadeh et al., 1996). A classic set is a crisp set with a crisp boundary. For example, a classical set A of real numbers smaller than 8 can be expressed as below:

$$A = \{x|x < 8\} \quad (1)$$

It is very clear and unambiguous boundary 8 such that if x is smaller than this number, then x belongs to this set A; or otherwise x does not belong to A. Classical sets are useful for various applications nevertheless they are too abstract and imprecise to reflect the human nature of thoughts. In spite of classical sets, a fuzzy set, as what its name shows, is a set without a crisp boundary. In fuzzy sets, members have transitions between “does not belong to a set” and “belongs to a set” smoothly. Membership functions define this gradual transition. They make it flexible to modeling common physical values by linguistic expressions such as “speed is low” or “current is high”. The term fuzz does not imply that members of a set are random values. But it refers to uncertain nature of physical and concrete parameters in abstract belonging concepts (Zadeh et al., 1996).

3.1. Fuzzification

Fuzzifier measures input variables, scales and maps them according to membership function. By fuzzification input signals and variables are scaled to crisp input quantities with numerical values (fuzzy quantities) according to membership functions. Usually, shapes and numbers of membership functions are chosen by the user.

All membership functions have values between 0 and 1 implying on of belongings of a quantity to a fuzzy set. Value 0 indicates that the quantity does not belong to the set absolutely and value 1 implies that the quantity belongs to the fuzzy set certainly. As what's discussed, M.F. parameterizes fuzzy set completely. Since most fuzzy sets have a universe of discourse X consisting of the real line R, it would be impractical to list all the pairs defining a membership function. So a M.F. is expressed with the help of a mathematical formula. A MF can be parameterized regarding to the complexity required.

3.2. Rules

Proposing the concept of linguistic or "fuzzy" variables by using fuzzy variables(Zadeh, 1973) claim that nouns can be used for sensor inputs such as "pressure," "displacement," "flow," "temperature," and "velocity". The fuzzy variables are adjectives that describe the variable (e.g. "largely negative" error, "small negative" error, "zero" error, "small positive" error, and "largely positive" error). For describing an error, one at least may simply have "positive", "zero", and "negative" variables for each of the parameters. For more comprehensive model additional ranges such as "very large" and "very small" could also be included which can be omitted in a basic system.

After the definition of linguistic variables and values, the rules of the fuzzy inference system can be formulated. These rules map the fuzzy inputs to fuzzy outputs. This mapping takes place through the compositional rule of inference, which is based on Zadeh’s extension of modus ponens, which is nothing more than the familiar if-then conditional form. A fuzzy if-then rule (also known as fuzzy rule) assumes the form If x is A then why is B, where A and B are linguistic values defined by fuzzy sets on the universe of discourse X and Y, respectively. “x is A “ is called the antecedent or premise, while “y is B” is called

the consequent or conclusion. This rule is also abbreviated as A → B. The antecedent normally consists of some combination of the inputs and the consequent consists of output variables (Zadeh et al., 1996). The antecedent takes the form:

$$\tilde{u}_1 \text{ is } \tilde{A}_1^j \text{ and } \tilde{u}_2 \text{ is } \tilde{A}_1^k \text{ and}, \dots, \tilde{u}_n \text{ is } \tilde{A}_n^k \quad (2)$$

where

$$\tilde{A}_i = \left\{\tilde{A}_i^j : j = 1,2, \dots, N_i\right\} \quad (3)$$

$\tilde{A}_i^j$ is the jth linguistic value of the linguistic variable $\tilde{u}_i$ defined over the universe of discourse U_i. The linguistic variable $\tilde{u}_i$ and its linguistic value $\tilde{A}_i^j$ are combined with the other variables and values on the antecedent by the fuzzy AND or OR operators. The choice depends upon the desired inference system. The AND operator corresponds to the intersection of the fuzzy sets and the OR operator corresponds to the union of the fuzzy sets. The antecedent need not require all linguistic variables and indeed could contain as few as one. The consequent takes the form

$$\tilde{y}_i \text{ is } \tilde{B}_i^p \quad (4)$$

where

$$\tilde{B}_i = \left\{\tilde{B}_i^p : p = 1,2, \dots, N_i\right\} \quad (5)$$

,$\tilde{B}_i^p$ is the pth linguistic value of the linguistic variable $\tilde{y}_i$ defined over the universe of discourse Y_i. Assuming all premise terms are used in every rule and a rule is generated for each possible premise combination, number of total rules will be:

$$\prod_{i=1}^{n} N_i = N_1 . N_2 . \dots . N_n \quad (6)$$

where n represents the number of linguistic variables in the antecedent and Ni is number of linguistic values per variable (Zadeh et al., 1996).

3.3 Defuzzification

Different defuzzification techniques exist, but the most commonly used are the centroid and the weighted average, respectively. The centroid method tries to determine the point at which a vertical line slices the combined set into two equal parts. This point is known as the center of gravity (C.O.G.) and its mathematical expression is shown below:

$$COG = \frac{(\sum \mu_a(x) * x)}{\sum \mu_a(x)} \quad (7)$$

where $\mu_a(x)$ is the MF of fuzzy set A for the crisp value x. The weighted average (W.A.) method calculates a defuzzified value using the following mathematical expression:

$$WA = \frac{\mu(x_1) \times x_1 + \mu(x_2) \times x_2 + \dots + \mu(x_i) \times x_i}{\mu(x_1) + \mu(x_2) + \dots + \mu(x_i)} \quad (8)$$

where $\mu(x_i)$ is the fuzzified input corresponding to the appropriate crisp value xi for each input fuzzy set. The election of cluster-heads requires a new fuzzy expert system.

In general, the steps for developing a new fuzzy expert system are: define appropriate linguistic variables, determine the fuzzy sets, define the rules, encode the fuzzy sets and rules in order to perform fuzzy inference, and, finally, evaluate the system. The linguistic values are the input variables to the system, the total number of rules depends on the number of input variables according to the rule n^k where k is the number of input variables in the system and n is the number of membership functions of each fuzzy set.

4. Results and Discussion

The cases are examined in this study is selected from the Asia and Pacific countries that experienced at least two huge financial crises in their economic history. There is no doubt the banking system sustained the shocks and after effects arose from the financial system as well. The periods of 1997-8 and 2007-8 were the years of crisis in the region as well as the other parts of the world. Considering the trend of basic indicators in different markets of the mentioned economies, dramatic turbulences can be seen around the period of both crises. This may be a witness of the contagion phenomenon in the region significantly when it is analyzed with respect to the global economy.

The data set used for this project consists of Australia, China, Japan, South Korea, Malaysia, New Zealand, and Singapore in the period of 1990-2009. The data are extracted from IMF, World Bank and Econstat databases and it is a compound of signal variables in the three levels of the total economy, financial sector and the banking sector. The list of signal variables and their definitions are shown in Appendix 1.

The selection of the explanatory variables is based on the different kinds of literature listed in previous research and the popularity of the variable usage. Also, it is based on the

data availability in the selected countries. It should be mentioned in the cases with missing data, a method of interpolation and extrapolation is applied to simulate the data. In most of the studies, the focus is just on one or two aspects of the crisis and there are few types of research which try to consider the crisis as a contagious phenomenon.

In this study, the banking sector is not assumed as an isolated market and despite the data limitations, the effort is to consider all the factors may lead to the critical situations. Therefore, entering lots of explanatory variables in the model limits the usage of prevalent statistical methods where these methods are not that much successful in analyzing the historical behavior of the variables. In fact, the statistical models are constructed on classical assumptions which limit their ability in explaining the dynamic variations.

Our initial approach employed to analyze the behavior of the signal variables is Fuzzy and the crisis index defined according to the (Hanschel & Monnin, 2005) EWS study. In order to construct an index for determining the crisis, there is a need to combine all the variables together and transform them to a unique variable that is the representative of the crisis. To come up with the problem of different weights the approach of variance equal weights is applied to devote equal weights to each variable. This way the difference between every variable and its average is divided by the standard deviation to approach the standardized X:

$$SX = ABS\left(\frac{X-\bar{X}}{\delta}\right) \tag{9}$$

The absolute value is constructed to avoiding of canceling off the negative and positive effects in the index. Lastly, the distress index will be calculated as below:

$$Y_t = \sum_{t=1}^{t} SX_t \tag{10}$$

Next step is the heart of analysis of this project. At this step, a differentiation is applied to each successor Yt. In mathematical explanation, it is defined as below:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{11}$$

Based on principle differential definition, ΔY_t is defined the slope or change in each year and also can be used to predict the rate of variations in the coming year. In fact, the slope shows the intensity of the crisis; the more amount of slope –either negative or positive- the more tensity of the crisis. In a simple illustration, the estimation of next year distress index can be defined as:

$$\hat{Y}_{t+1} = Y_t + \Delta Y_t \tag{12}$$

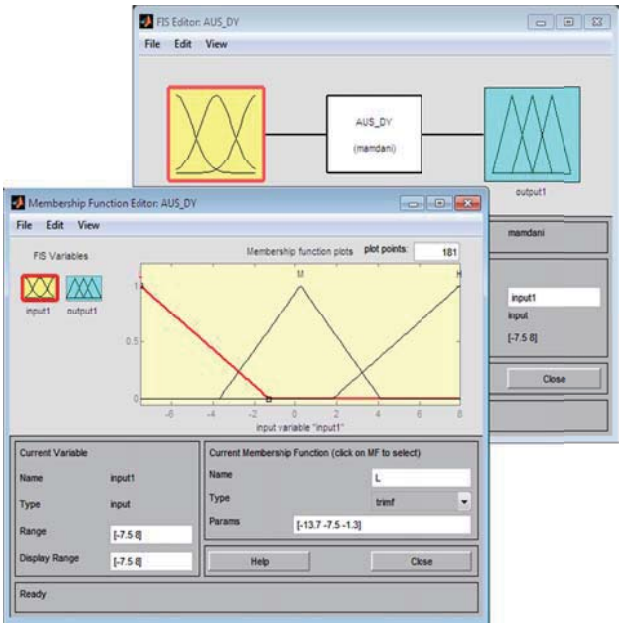
Where $\hat{Y}_{t+1}$represents the estimated distress index in the coming year. Besides providing the slope, the average and the respective standard deviation of each year's distress index are provided to be implemented in the Fuzzy logic estimator function.

The first fuzzy logic estimator function is the defined basis on this slope. It means, the slope is the input of the Fuzzy Logic Estimator function, and this input is verified regarding the average and calculated a standard deviation. In the project definition, if the input of the function, slope, is in the range, $\bar{X} - \delta < \Delta Y_t < \bar{X} + \delta$ the coming next period risk is low and if the slop is out of the range, $\Delta Y_t < \bar{X} - \delta$ and $\Delta Y_t > \bar{X} + \delta$ the next coming period risk is high. The rule of this fuzzy function is defined as below:

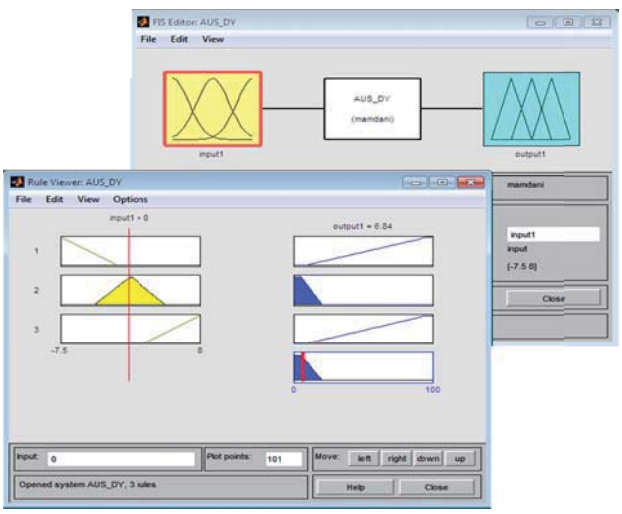
$$\begin{cases} \text{If INPUT is MEDIUM then OUTPUT is LOW} \\ \text{If INPUT is LOW then OUTPUT is HIGH} \\ \text{If INPUT is HIGH the OUTPUT is HIGH} \end{cases} \tag{13}$$

The next step is defining our member functions and the respective ranges. In Australia case, for example, in the year of 2009, the average is 0.234 and the standard deviation is 3.877; according to equations, the confidence range is between $0.234 - 3.877$ and $0.234 + 3.877$ equals between -3.643 and 4.111 defining the input medium member function, considering the middle point equals to average number, 0.234.

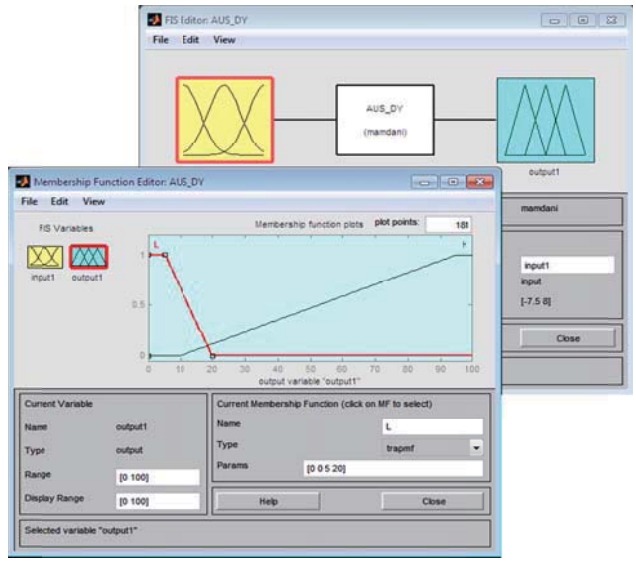
In the project, the lowest critical range is defined as $\bar{X} - (2 * \delta)$and the highest critical range is defined as$\bar{X} + (2 * \delta)$, so the lowest and highest critical ranges equal to $0.234 - (2 * 3.877) = -7.52$ and $0.234 + (2 * 3.877) = 7.99$ respectively. It is clear all lower or higher values than the ranges are rounded to the nearest in range value. The output is constituted of two member functions, High and Low, considering the lowest value is 0, equals to 0% and the highest range is 100, which equals to 100%. The Low member function range is between 0 to 20, and the High member function range is between 10 to 100. In fact, the final result of the designed system indicates the probability of the coming period crisis. Regarding the aforementioned, the resulted Input and Output member functions, and rules are shown in Figures 3 to 5.



<Figure 3> Fuzzy Logic Input Member Functions



<Figure 4> Fuzzy Logic Rule Definition



<Figure 5> Fuzzy Logic Output Member Functions

The fuzzy logic function is extended for all selected countries by the same construction procedure. The resulted crisis probability for those countries in 1997, 2007, and 2010 are provided is Tables 3 to 5 respectively. Based on principle differential definition, ΔY_t Is defined as the slope or change of index in each year and also can be used to predict the rate of variations in the coming year. In fact, the slope shows the intensity of the crisis; the more amount of slope –either negative or positive- the more the intensity of the crisis." This amount shows the power of the shock.

<Table 3> Crisis Forecasting for 1997

Country	ΔY_t	Average	ST Deviation	Probability
Australia	0.756	-2.39	3.107	63%
China	-3.436	-1.657	4.404	8%
Japan	-3.323	-2.540	1.937	8%
S. Korea	-2.492	-0.467	2.408	53%
Malaysia	4.826	3.079	6.912	8%
New Zealand	-2.412	1.142	5.283	7%
Singapore	-0.387	-1.192	3.576	7%

As the table above show ΔY_t can be a proper signal of crisis resulted in the cases that this amount shows a peak the probability of the crisis which estimated by the system also rises and vice versa. In 1997, South Korea recorded higher probability to have a banking crisis from the EWS. South Korea had a large foreign debt denominated in US dollars in 1997. In the hindsight, Korean Won tumbled in low value after the Asian financial crisis struck in July 1997. China and Japanese banking system are also vulnerable.

<Table 4> Crisis Forecasting for 2007

Country	ΔY_t	Average	ST Deviation	Probability
Australia	4.315	-0.786	3.094	68%
China	4.635	-0.432	3.511	67%
Japan	0.388	-0.671	2.286	8%
S. Korea	0.287	0.324	4.064	7%
Malaysia	1.894	0.632	4.966	7%
New Zealand	5.212	0.711	4.233	63%
Singapore	1.665	-0.233	4.298	8%

In 2007, China, Australia and New Zealand banking systems appear to be vulnerable to crisis. The surge of China export, the influx of FDIs and booming in the stock market are some of the signs of heated economy.

<Table 5> Crisis Forecasting for 2010

Country	ΔY_t	Average	ST Deviation	Probability
Australia	8.914	0.234	3.877	70%
China	4.991	-0.054	3.798	65%
Japan	6.042	-0.165	2.644	70%
S. Korea	0.277	0.467	3.737	7%
Malaysia	-1.013	0.138	4.744	7%
New Zealand	-5.494	0.391	4.148	67%
Singapore	2.35	0.664	4.671	8%

Similarly in 2010, Australia, China, Japan and New Zealand banking systems appear to be exposed to the high chance of the crisis. Japan with internal problem of deflation and stagnant economic growth, coupled with the high value of Yen in international market exposes its economy to slow growth and higher non-performing loans in the banking sector.

As it can be seen in the tables mentioned in all the years covered in the results, the big economies have more exposure to the crisis. It may be because they are more dependent on the global economy. The other reason is because they are big economies with higher GDP and M3, the shocks are more prevalent in these countries. It can be said that there is no guarantee that developing economies can get rid of the crisis and the costs may be higher.

5. Conclusion

In this study, we tried to develop an early warning system that can recognize the crisis and determine the power of it according to the historical changes of the variables. The advantage of this study compared to the previous studies is the variety of the variables implied. However, this can be considered as a disadvantage if the employed modeling approach could not explain the behavior of the variables logically as statistical models lose their efficiency when a number of variables goes up. The problem of stationary is the other limitation for using these models.

This way, in order to solve the problem we employed a fuzzy approach to get rid of the time-consuming statistical analyses. Indeed, the fuzzy approach provides us the possibility of describing the shocks without engaging with the limitations of data and statistical models. On the other hand, most of the studies used mathematical approaches such as fuzzy logic have employed just a few variables in their analyses because of the limitation of logic model and processing. In this study, defining a comprehensive index of crisis we consider a wide variety of important variables in different economic dimensions and use it as a tool for modeling the crisis that relies on fuzzy logic theory.

Our results show, firstly, in 1997, South Korea recorded higher probability to have a banking crisis from the EWS. South Korea had a large foreign debt denominated in US dollars in 1997. Secondly, in 2007, China, Australia, and New Zealand banking systems appear to be vulnerable to crisis. The surge of China export, the influx of FDIs and booming in the stock market is some of the signs of a heated economy. Australia with uncertainty prices in the commodity is also vulnerable to crisis. Thirdly, in 2010, Australia, China, Japan and New Zealand banking systems appear to be exposed to the high chance of a crisis. Japan with internal problems of deflation and stagnant economic growth, coupled with the high value of the yen in international market exposes its economy to slow growth and higher non-performing loans in the banking sector.

This way it can be claimed that our results show the defined signal of the crisis can properly illustrate the critical situations. In the cases when there is a shock in the crisis index, the probability of the crisis, which is estimated by the system also shows rising and vice versa. The other interesting issue is that the trend of the index completely can explain the behavioral changes of the studies economies.

Also, in the critical years, more powerful economies are exposed to a higher probability of a crisis and this issue obviously shows the urgent need of crisis monitoring in big economies.

This way it can be said there is no guarantee that powerful economies are immune from the crisis and the cost may be higher.

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