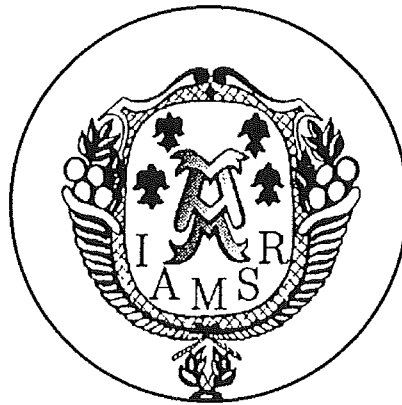


# RESEARCH REPORTS

## Fuzzy Clustering Analysis of the Early Warning Signs of Financial Crisis

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Research Report 1/2003



Institute for Advanced  
Management Systems Research

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**Abstract:** The fuzzy logic approach offers us the means to deal with uncertainty inherent in a wide variety of tasks, to treat vague and imprecise linguistic values, and to model nonlinear relationships. In this paper we apply fuzzy clustering methods and tools to the evaluation of early warning indicators of financial crises. We first provide the relevant background domain knowledge and then present the fuzzy clustering approach that we used. We also give empirical results from the fuzzy clustering analysis of the Finnish currency crisis in 1992.

## 1. Introduction

With the deregulation of international capital flows, financial crises have become a major threat to macroeconomic stability. In the context of this paper, a financial crisis is defined as a situation where massive capital outflows force a country to devalue or float its currency.

The theoretical research on financial crises can be divided into two main categories. According to the 'fundamentals' approach first outlined by Krugman (1979), a financial crisis is the result of certain fundamental imbalances that eventually lead to a balance of payments crisis, thus depleting official foreign exchange reserves. The so-called second generation of financial crises theory (e.g. Obstfeld, 1986), again, focuses on the role of self-fulfilling expectations. It should be noted, though, that these two approaches are by no means mutually exclusive: whereas experience has shown that expectations of a devaluation or floating of a currency eventually become self-fulfilling, it is equally true that speculative attacks against fixed exchange rates are generally triggered by severe imbalances in economic fundamentals, notably the current account. In addition, the economic growth rate, real exchange rate, level of foreign exchange reserves, share of short-term loans in the total outstanding foreign debt and the state of the banking system can also serve as potential early warning signs of impending financial crisis.

Although the early warning signals as such are commonly known, financial crises still tend to take investors by surprise. Such a fact does, for its part, imply that the timing of a financial crisis is extremely difficult to forecast with any accuracy and early enough to leave time for taking precautions. Another reason for this is probably the lack of appropriate instruments for the systematic monitoring and analysis of these economic variables. The work on financial crises has thus far been dominated by either theoretical or descriptive / qualitative analysis. Among the empirical studies, the most ambitious ones are Kaminsky and Reinhart (1999) and Goldstein, Kaminsky and Reinhart (2000). In order to find the link between banking and currency crises as well as the underlying common patterns of the crises, Kaminsky and Reinhart (1999) studied the behaviour of macroeconomic indicators around crisis periods, based on a chronology of events in the banking and external sectors related to 76 currency crises and 26 banking crises spanning the 1970's through 1995. They assessed the fragility of economies around the time of the financial crises using statistical methods. McNelis (1998) examined the relationship between monthly currency and quasi-money demand, financial distress and exchange rate uncertainty in Indonesia from 1984 to 1997, using both linear and neural network models.

As major financial crises have been relatively few and far between, traditional econometric analysis tools (e.g. linear regression models, or simple probability models) offer only limited help when it comes to the assessment of their leading indicators in a systematic way. Purely linear specifications that are frequently used for simplicity cannot recognize complex non-linear dynamics and do not perform well with higher frequency data (Lindstrom, 1997; McNeils, 1998;). The fuzzy logic approach on the other hand offers us the means to deal with uncertainties and to model nonlinear relationships among variables. There is no

need to assume anything about the functional form of a hypothesized relationship between input and output variables. In our research, we propose that fuzzy logic is a relevant approach to the modeling and analysis of early warning signs of financial crises.

Fuzzy set and fuzzy logic have found extensive application in many fields, especially in engineering as well as in finance. However, it seems that so far there has been very little application to the analysis of economic problems and economic data until very recently (Lindstrom, 1998; Shepherd and Shi, 1998; Draeseke and Giles, 1999, 2000, 2001). On the other hand, often we have to deal with complex relationships between economic variables that are non-linear and very difficult to discover from data and to describe using conventional mathematical modeling methods.

In this study we shall apply fuzzy logic to the modeling and analysis of key economic fundamentals and to describe their relationships. Specifically, we look at how we can apply the Fuzzy C-Means (FCM) based fuzzy clustering method to identify the critical levels of the important economic variables. The rest of the paper is organized as follows. In Section 2, we discuss the assessment of early warning information of financial crises. In Section 3, we present our overall methodology and discuss the issues that arise when using the fuzzy clustering approach. In Section 4 we present the results of an empirical study of the Finnish currency crisis in 1992. Section 5 concludes the paper.

## 2. The Evaluation of Early Warning Indicators of Financial Crises

Financial crises are typically preceded by a multitude of weak and deteriorating economic fundamentals. The cases of crises where the economic fundamentals were sound are rare (Kaminsky and Reinhart, 1999). In this section, the economic theory on each of the economic fundamentals that may serve as early warning indicators of a financial crisis are presented in closer detail. In the table below we give a summarization and formal definition of variables that we consider to be most relevant.

<i>Table 1 Variable Definitions</i>			
<b>Input Variables</b>			
<i>Current Account</i>			
<i>Variable name</i>	<i>Description</i>	<i>Value Range</i>	<i>Value Terms</i>
CurrentAccountDeficit Level (CADL)	As percentage of GDP	[-10, 10]	very high, high, medium, low, very low
Total Net Foreign Debt (TNFD)	As percentage of GDP	0-300	Very low, low, medium, high, very high
<i>Foreign Exchange Reserves</i>			
ForeignExchangeReserves Level (FERL)	Money value of foreign exchange reserves	bn USD	Very good, good, ok, low, very low
<i>Economic Growth</i>			
Growth Rate (EGR)	Percent growth of GDP from previous quarter	[-10, 10]	very high, high, normal, below normal, very low
<i>Real Exchange Rate</i>			
Rate of Change (RERR)	Percent deviation of the real exchange rate from January 1, 1983 <sup>1</sup>	[-100,10]	Very positive deviation, positive deviation, no deviation, negative deviation, very negative deviation
<i>State of Banking System</i>			
Overall State (OSBS)	Qualitative measure	0-100	badly run, highly vulnerable, well run,
<b>Output Variables</b>			
<i>Financial Crises</i>			
Number of Early Warning Signals (NEWS)	Count the number of signaling variables	0-10	No signal, a few signal, some signal, many signal, all signal

<sup>1</sup> After two consecutive devaluations in October 1982, the real effective FIM exchange rate was close to PPP at the beginning of 1983.

**The Current Account Deficit:** A current account deficit in itself does not necessarily indicate an imminent risk of a financial crisis. For example, a current account deficit financed mainly through inward foreign direct investment (FDI) can be seen as a normal transitory phase of capital-poor emerging markets.<sup>2</sup> By contrast, a deficit that is financed mainly through foreign borrowing – particularly if borrowing is predominantly short-term – may easily lead to a vicious circle where the servicing costs of the foreign debt widen the deficit further still.

As a general rule, a current account deficit becomes critical when it exceeds 5 per cent of GDP. However, even a deficit in excess of this ‘critical level’ may not necessarily lead to an eventual financial crisis as long as it is financed in a sustainable manner.

**Foreign Exchange Reserves:** The level of foreign exchange reserves is a key element in the model of Krugman (1979). Experience has shown that the defence of a significantly overvalued exchange rate is doomed to fail eventually, no matter how much reserves the central bank has at its disposal for defending the exchange rate peg. However, the level of foreign exchange reserves provides the most important indication of the central bank’s ability to support the exchange rate peg in the short run, as well as a potential indication as to the timing of the collapse of the exchange rate regime. And the kind of massive capital flight that usually precedes the collapse of an exchange rate peg would, for its part, show up as a rapid deterioration of foreign exchange reserves.

**The Real Exchange Rate:** The typical victim of a financial crisis is an open economy with a fixed exchange rate that has become significantly overvalued. In most cases, the appreciation of the real exchange rate would be the result of failure to contain domestic inflation. However, it may also, at least partly, be explained by the appreciation of the anchor currency (as in the South-East Asian crisis of 1997-98) or by beggar-thy-neighbour devaluations of other countries in the same region (Argentina vs Brazil in the late 1990’s).

Experience has shown that an overvalued currency can be defended only for so long. Although the eventual adjustment towards Purchasing Power Parity is inevitable, the question of timing is far more difficult to answer, however. In other words, is there, as in the case of the current account deficit, a ‘critical level’ for exchange rate overvaluation as well, either in terms of magnitude or duration, or both?

**Economic Growth:** Countries displaying exceptionally high economic growth (the South-East Asian “tiger economies”, the US) can easily attract foreign investment, and thus finance even quite substantial current account deficits for several years. However, when growth rates decline, foreign capital flows tend to dry up very quickly, in which case the country in question either has to make the necessary adjustments in order to reduce its current account deficit or resort to foreign borrowing. The former alternative would be economically painful in the short run as it – precluding a devaluation in order to boost exports and reduce imports – means increasing domestic saving (public or private) in a situation where the economy is already in a cyclical downturn or even in an outright recession. The latter alternative, for its part, contains the risk of a ‘vicious circle’ where interest payments on the mounting foreign debt will add to the current account deficit, which in turn leads to more foreign borrowing and so on.

**State of the Banking System:** In many cases (South-East Asia, Argentina), victims of financial crisis have had badly run and highly vulnerable banking systems. The main problems have been a high share of non-performing loans (loans where the debtor is unable to pay either interest or capital), and substantial foreign borrowing by domestic banks. Especially the latter problem makes it difficult for a country with fixed exchange rates to devalue or float its currency; when domestic banks have a lot of foreign-currency debt and mainly domestic-currency assets, a strong exchange rate depreciation would likely lead to a costly and painful banking crisis. As far as emerging markets are concerned, the vulnerability of the banking sector would, in addition, often be exacerbated by the fact that a high share of domestic debt is denominated in foreign currency as well (Mishkin, 1999).

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<sup>2</sup> As the experience of the South-East Asian crisis in 1997-98 shows, however, the current account deficit may still become a problem if, for some reason, inflows of FDI suddenly dry up.

Yet another characteristic of the banking sector in many emerging markets is the *de facto* mismatch between foreign currency-denominated assets and foreign currency-denominated liabilities. Even where prudential banking regulations oblige banks to match their foreign currency-denominated assets and liabilities, such mismatches may still occur. In emerging markets, the foreign currency-denominated assets of domestic banks would mainly be foreign currency loans to domestic companies. In the event of a devaluation, many of these loans would turn non-performing due to the adverse effects on the balance sheets of domestic companies (who have most of their assets in domestic currency while their debts are predominantly foreign-currency denominated) (Ibid.).

Finally, so far we have examined the main economic fundamentals individually. It is clear, however, that it is the combined effect of several or all of these variables at the same time that eventually triggers off a financial crisis. It is equally clear that there is no unique level of these combined effects beyond which the defence of an exchange rate peg becomes unsustainable; due to a number of country-specific factors – economic, political and institutional – one country may successfully defend its exchange rate where another one caves in almost immediately. Still, it seems plausible to assume that there are some common criteria for when the threat of a financial crisis and subsequent exchange rate collapse becomes imminent.

### 3. Using Fuzzy Clustering Method in the Analysis of Financial Crisis Signals

#### 3.1 Fuzzy Clustering Methods and Fuzzy C-Means Algorithm (FCM)

Clustering methods and techniques offer us the means to group data points, which can represent multidimensional data, into natural clusters such that the clusters will show an underlying pattern hidden in the data. Applying fuzzy clustering methods, data points can be partitioned into overlapping natural groups, that is, fuzzy clusters where each data point belongs to each cluster to some degree that is specified by a membership value. Fuzzy clustering method has been used extensively for tasks such as pattern recognition, data mining, and fuzzy modeling from data.

The Fuzzy C-Means Algorithm (FCM) implements an objective function based fuzzy clustering method. It was originally developed by Jim Bezdek in 1981 as an improvement of earlier clustering methods (Bezdek, 1981). It can partition data pairs or data points in a multidimensional space into a specific number of fuzzy clusters. The algorithm starts with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster. It also assigns every data point a membership grade in each cluster indicating the degree of its association with the cluster. It is then an iterative process of adjusting the cluster centers and the degree of membership to each cluster for each data point. The initial guess of cluster centers is most likely incorrect. But by iteratively updating the cluster centers and the membership grades for each data point, FCM will eventually move the cluster centers to the “right” center location within a data set. The iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by the membership grade of the data point. After every iteration, the objective function will be improved. The iteration stops when the minimum amount of improvement between two consecutive iterations is less than a small positive number  $\epsilon$ . The output of the FCM process includes the cluster centers as well as the degree of membership for every data point in every cluster.

To summarize, there are basically four steps for using the FCM algorithm (Giles and Draeseke, 2001):

1. Select the initial location for the cluster centers.
2. Generate a new partition of the data by assigning each data point to its closest cluster center
3. Calculate new cluster centers as the centroids of the clusters
4. If the cluster partition is stable then stop. Otherwise go to step 2.

In Klir and Yuan (1995) and Giles and Draeseke (2001), we also find good descriptions of the mathematical foundations of FCM.

Let  $n$  be the number of data points;  $c$  be the number of fuzzy clusters (where  $n > c$ ). FCM can divide up the  $n$  data points into  $c$  clusters while at the same time determining the locations (centers) of these clusters in the appropriate space.

Let  $x_k$  be the  $k$ 'th vector data point ( $k = 1, 2, \dots, n$ ), let  $v_i$  be the center of the  $i$ 'th fuzzy cluster ( $i = 1, 2, \dots, c$ ). The objective function is formulated based on "squared error distance". Let  $d_{ik} = \|x_k - v_i\|$  be the distance between  $x_k$  and  $v_i$ , and  $u_{ik}$  be the degree of membership of data point  $k$  in cluster  $I$ , where

$$\sum_{i=1}^c (u_{ik}) = 1$$

The objective function is then formulated as:

$$J(U, v) = \sum_{i=1}^c \sum_{k=1}^n (u_{ik})^m (d_{ik})^2$$

Membership values for each data point are determined by:

$$u_{ik} = 1 / \left\{ \sum_{j=1}^n \left[ (d_{ik})^2 / (d_{jk})^2 \right]^{1/(m-1)} \right\}$$

Cluster centers are updated by:

$$V_i = \left[ \frac{\sum_{k=1}^n (u_{ik})^m x_k}{\sum_{k=1}^n (u_{ik})^m} \right]; i = 1, 2, \dots, c$$

The algorithm is based on an assumption that the desired number of clusters  $c$  is given and  $m$  is a real number  $m \in (1, \infty)$ , called the exponent parameter. It is selected according to the problem under consideration. When  $m \rightarrow 1$ , the fuzzy  $c$ -means converges to a classical (crisp)  $c$  means ( $m = 1$  result in crisp clusters). To the other direction, the partition of data becomes fuzzier with increasing  $m$ . When  $m \rightarrow \infty$ , all cluster centers tend towards the centroid of the data set. There seems to be no theoretical basis for an optimal choice for the value  $m$ . But most often  $m = 2.0$  is the common choice.  $\epsilon$  is a small positive number serving as the stopping criterion for the FCM iterations.

### 3.2 Using Fuzzy Clustering Methods in the Analysis of Financial Crisis Signals

In the literature of economic studies, so far it has been very difficult, if not completely impossible, a task to pinpoint the *timing* of a financial crisis. In other words, it is very difficult to tell when does the sum of economic imbalances – an overvalued exchange rate, a growing current account deficit, dwindling foreign exchange reserves and so on – become critical enough to trigger a shift in the exchange rate regime? While such difficulties in pinpointing the exact timing of an impending crisis has been acknowledged, here we shift our focus to the identification of a "point of no return", i.e. a (combined) critical level of the economic fundamentals beyond which it is simply impossible to maintain a fixed exchange rate regime. Whereas this would not allow us to pinpoint the exact timing of a crisis, it would still allow us to identify situations where a crisis is no longer avoidable.

Again, to define the "point of no return" in terms of economic fundamentals seems to be not a very straightforward job to do either. However, when we look back and have an examination of previous cases of financial crises, it is quite easy for us to tell precisely when is the "point-of-no return". If we can grasp the feature and characteristics of the economic variables at the time of crisis, at the time of healthy economic development, at the time of pre-crisis and at the time of after-crisis, it will certainly help us to understand the state of economic fundamentals at or near the point-of-no-return. We consider that a fuzzy clustering analysis of the economic data covering both the crisis and non-crisis time could help us to find out features of the economic fundamentals at different time periods, and lead us to the identification of the critical levels of fundamental imbalances.

## 4. Fuzzy Clustering Analysis of the Finnish Currency Crisis in 1992

### 4.1 The Finnish Currency Crisis in 1992

Having pursued an active exchange rate policy based on frequent devaluations since the end of WWII, Finland adopted a stable exchange rate regime – the so called ‘strong markka regime’ – in 1983. The FIM was pegged to a currency basket including the currencies of Finland’s main trading partners and, in June 1991, to the ECU basket.

However, due to high inflation and excessive wage increases in the export industries, the FIM had become significantly overvalued by the beginning of the 1990’s. As, in addition, the Finnish economy was hit by two severe external shocks, the collapse of trade with the Soviet Union and the recession in Western Europe, pressures on the exchange rate peg started to mount very rapidly. The FIM was first devalued by 14 per cent in November 1991, but this measure was clearly too little and too late to stabilize the situation in the foreign exchange market and dampen expectations of further currency depreciation. On September 7, 1992, the markka was then finally floated, and subsequently depreciated by around 30 per cent before stabilizing again in March 1993.

### 4.2 The Fuzzy Clustering Analysis

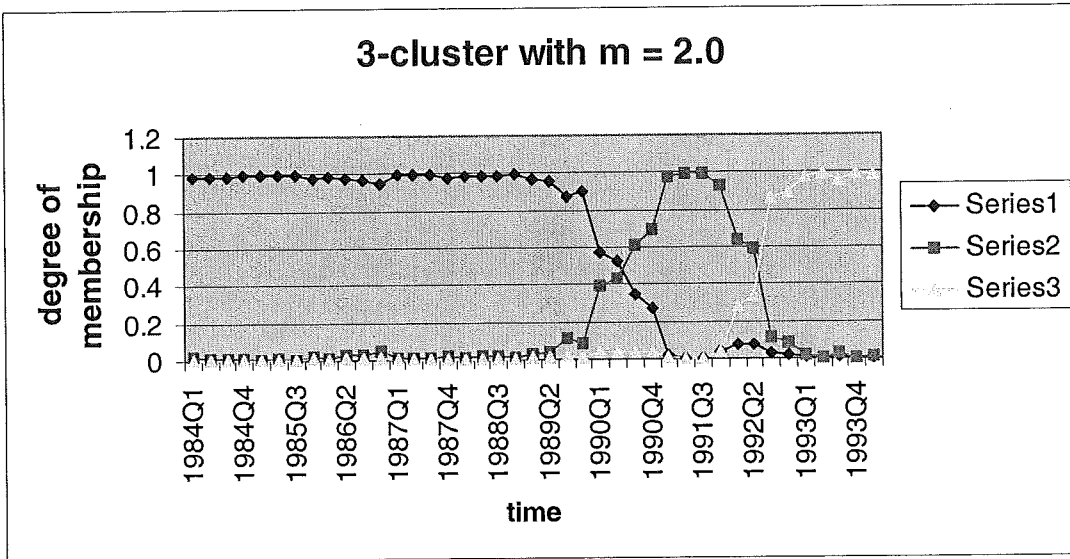
The Matlab Fuzzy Logic Toolbox allows us to easily use the FCM clustering techniques. Using the toolbox, we carried out a number of experiments to do data clustering analysis of the Finnish economic fundamentals surrounding the currency crisis in 1992. Data were collected for each of the variables defined in Table 1. Due to time constraints we were not able to obtain data on the state of banking systems as well as data on the output variable. So the analysis reported here covers all the other variables (current account deficit as a percentage of GDP value, total net foreign debt as a percentage of GDP value, percent deviation of real exchange rate from year 19983 level, economic growth rate, and foreign exchange reserves in billions of dollars). The best data available are on a quarterly basis. We picked up 41 effective data points, from the first quarter of 1984 to the first quarter of 1994.

To start the clustering analysis, we need to specify the desired number of clusters first, which is usually not a very easy task for many clustering problems. However, in our case the clustering problem clearly implies what would be the meaningful number of clusters. For example, two clusters is one possibility, when we want to look at the data and see only how they differ during Crisis-Time and Non-Crisis-Time. With three clusters then, we could see the data be grouped into categories of Tranquil-Period, Early-Warning Period, and Crisis-Period. With four clusters, we could then distinguish Tranquil-Period, Early-Warning Period, Crisis-Period and Post-Crisis-Period. There is not much point to have more than 4 clusters. So  $c = 2, 3$  and  $4$  should be able to reflect the natural structure of the data. But some initial test shows that two clusters are too limited and could not describe the complexity in the data properly. So we choose to focus on only 3-cluster and 4-cluster analysis.

Another parameter that needs to be experimented with is the exponent  $m$ . We have tested a number of different  $m$  values (1.5, 1.8 2.0, 2.16, 2.6, 3.0) and dropped the results for  $m = 2.6$  and  $3.0$  as the resulted clusters appear to be too fuzzy to (for example with no data points assume a full membership in the Crisis Cluster). For other FCM parameters we have adopted the default values:  $\epsilon = 0.00001$ , and the maximum number of iterations is 100.

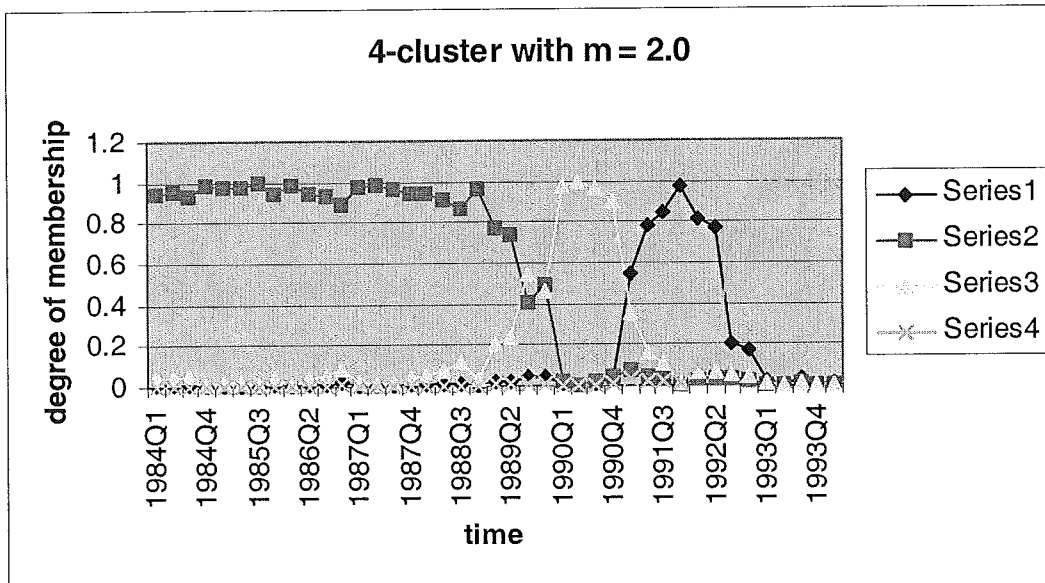
Below we presented three pair of empirical results: 3-cluster vs 4-cluster analysis with  $m = 2.0, 1.5$  and  $2.16$  respectively. The charts illustrate the degree of membership for each data point in each cluster. The tables below the charts specify the cluster centers. As we can see, with 3-cluster analysis, we were able to partition the data into three groups: Tranquil-Cluster, Crisis Cluster and Post-Crisis Cluster. With 4-cluster analysis, we were able to partition the data into four groups: the Tranquil-Cluster, Crisis Cluster and Post-Crisis Cluster, plus a cluster between the crisis and tranquil period, which we label as the Early Warning Cluster. If we look at the timing where the membership value associated with the crisis cluster equals to 1, we can find that it corresponds to the actual crisis time (or point of no return) rather well in almost all the tests.

### 3-cluster with m = 2.0



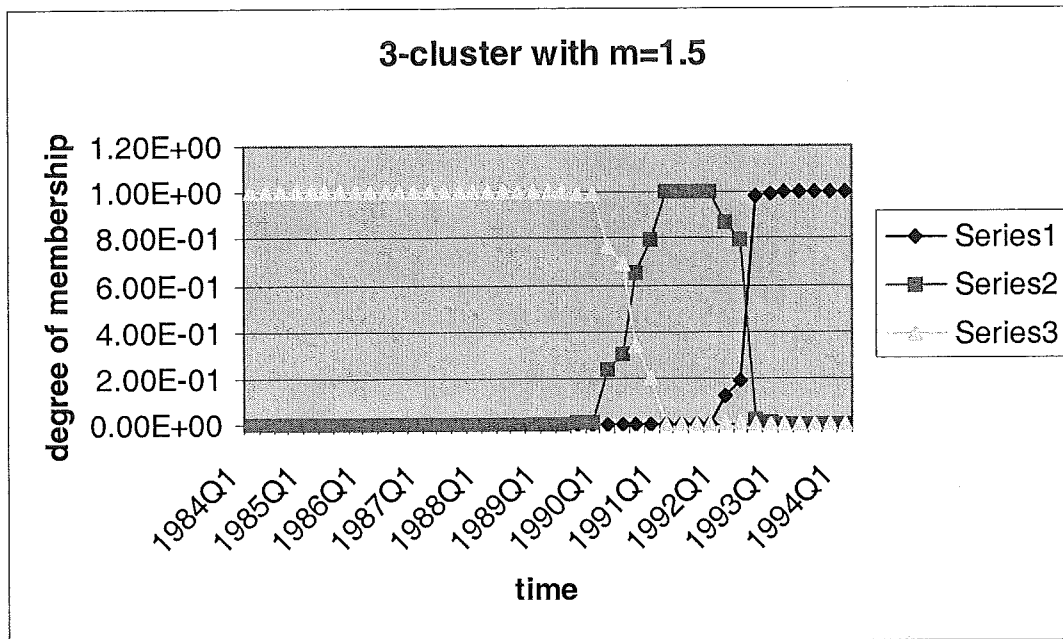
	Cluster Centers		M = 2.0			
Series 1	-1.9989	63.95	1.6164	3.7466	12.034	Tranquil Time
Series 2	-5.4615	130.34	-4.1406	-4.7963	20.992	Crisis Time
Series 3	-1.7494	213.79	-30.208	-1.0502	16.081	Post-Crisis

### 4-cluster with m = 2.0

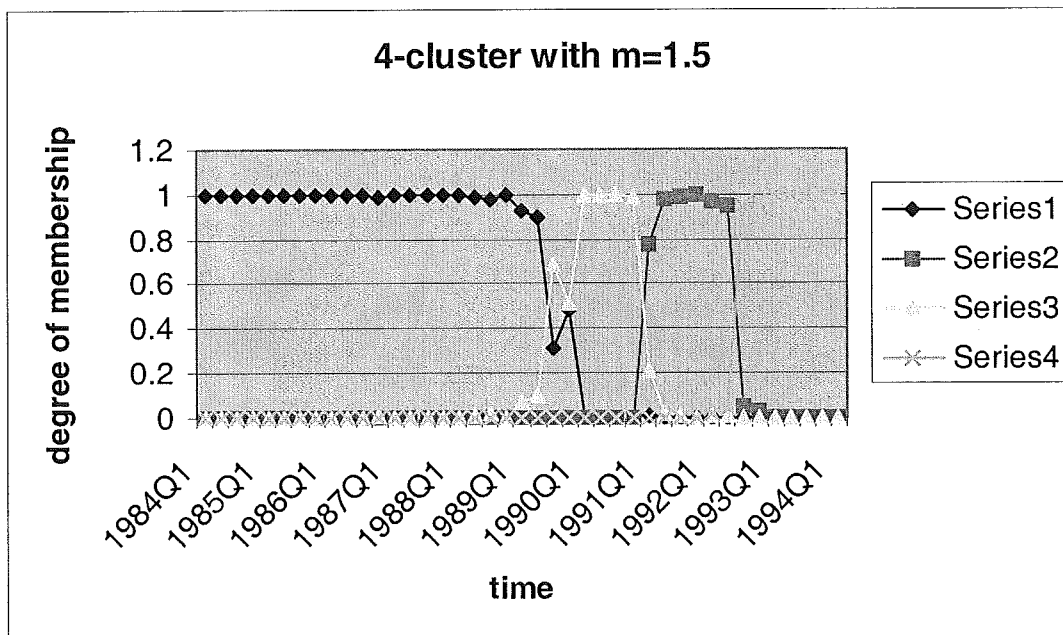


	Cluster Centers		M = 2.0			
Series 1	-5.3774	145.49	-9.9737	-5.5341	18.543	Crisis Cluster
Series 2	-1.59	61.487	1.3512	3.7086	11.123	Tranquil Clust.
Series 3	-5.1739	96.791	4.0294	0.71921	23.053	Early Warning
Series 4	-1.5179	216.81	-31.045	-0.85078	15.945	Post-Crisis

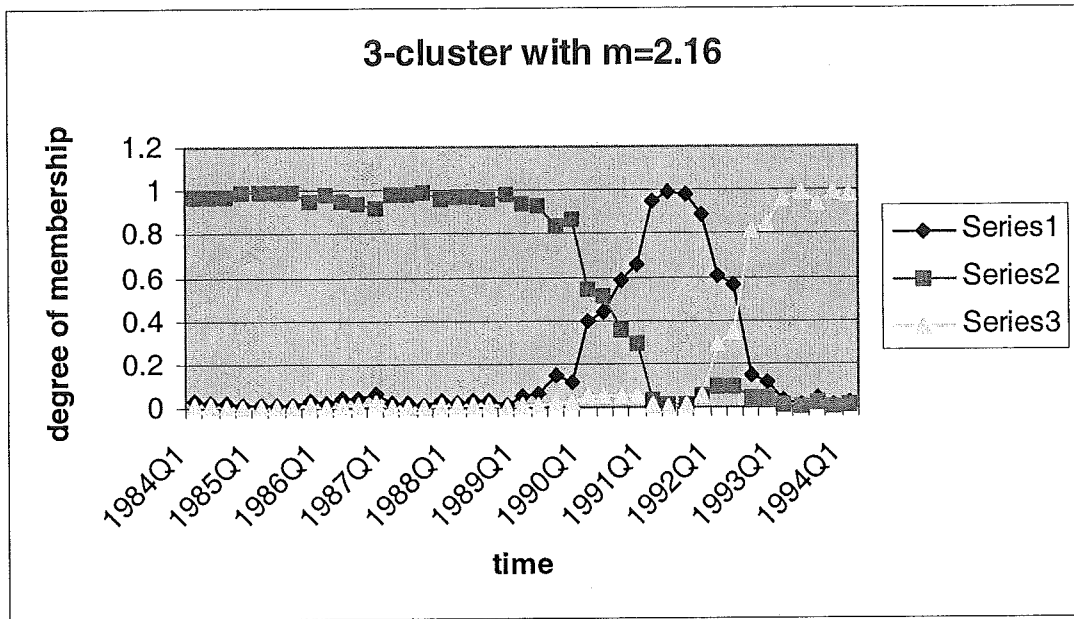




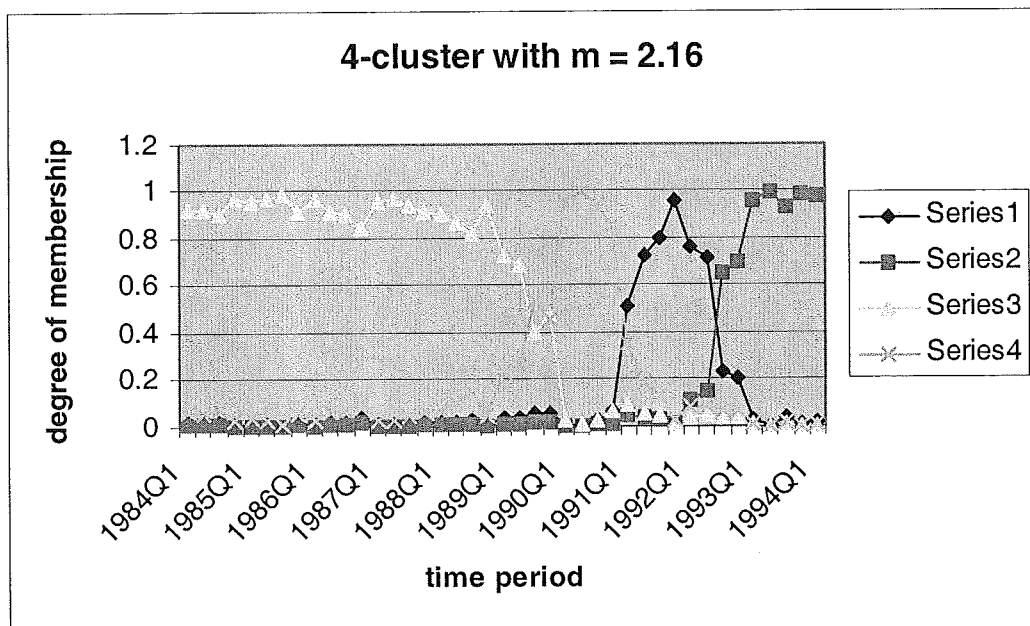
	Cluster Centers			M = 1.5			
Series 1	-1.78	213.45	-30.04	-1.1075	16.065		Post-Crisis
Series 2	-5.5323	133.03	-5.3183	-4.7316	21.035		Crisis Cluster
Series 3	-2.1346	64.932	1.7229	3.7219	12.365		Tranquil Clust.



	Cluster Centers			M = 1.5			
Series 1	-1.6708	61.707	1.3712	3.7658	11.341		Tranquil Clus.
Series 2	-5.5643	144.27	-9.1813	-5.5185	19.21		Crisis Cluster
Series 3	-5.2548	95.629	4.1793	0.98533	22.792		Early Warning
Series 4	-1.6942	214.53	-30.324	-1.0391	16.014		Post-Crisis



	Cluster Centers		M = 2.16			
Series 1	-5.4489	130.21	-4.0034	-4.8532	20.941	Crisis Cluster
Series 2	-1.9587	63.76	1.5958	3.7414	11.961	Tranquil Cluster
Series 3	-1.6982	214.33	-30.384	-0.99969	16.071	Post-Crisis



	Cluster Centers		M = 2.16			
Series 1	-5.3321	145.59	-10.124	-5.5512	18.372	Crisis Cluster
Series 2	-1.4535	217.56	-31.284	-0.78862	15.929	Post-Crisis
Series 3	-1.5577	61.41	1.3507	3.6872	11.037	Tranquil Cluster
Series 4	-5.1443	96.644	4.0000	0.77186	22.975	Early Warning

If we look at the data points that represent the cluster centers (shown below), we can notice that the Finnish currency crisis in 1992 was characterized by a current account deficit of 5.3% to 5.6% of GDP value, a net foreign debt of 130% to 146% of GDP, negative economic growth rate of -4.8% to -5.6%, and deviation of the exchange rate of -4% to -10% from the PPP level. Comparing to it, in the Early Warning Cluster, the foreign reserve level and the current account deficit are quite similar. The economic growth rate is between 0.7% and 1%, and total net foreign debt is around 96% of GDP value. These could indicate the critical levels that should be watched closely to detect an impending currency crisis.

<i>Center Points for the Crisis Cluster</i>				
Current Account	Net Foreign Debt	Real Exch. Rate	Economic Growth	Exchange Reserve
-5.4615	130.34	-4.1406	-4.7963	20.992
-5.3774	145.49	-9.9737	-5.5341	18.543
-5.5323	133.03	-5.3183	-4.7316	21.035
-5.5643	144.27	-9.1813	-5.5185	19.21
-5.4489	130.21	-4.0034	-4.8532	20.941
-5.3321	145.59	-10.124	-5.5512	18.372

<i>Center Points for the Early Warning Cluster</i>				
Current Account	Net Foreign Debt	Real Exch. Rate	Economic Growth	Exchange Reserve
-5.1739	96.791	4.0294	0.71921	23.053
-5.2548	95.629	4.1793	0.98533	22.792
-5.1443	96.644	4.0000	0.77186	22.975

## 5. Conclusions

In the analysis of early indicators of financial crisis, we have very limited knowledge of the quantitative relationships between the important economic variables while these relationships may be intrinsically non-linear and very complex. Especially, it has been a very difficult task to tell when does the sum of economic imbalances – an overvalued exchange rate, a growing current account deficit, dwindling foreign exchange reserves and so on – become critical enough to trigger a shift in the exchange rate regime. In this paper we tried to address this problem with the help of fuzzy clustering techniques. The FCM fuzzy clustering method allows us to group multiple economic time series data into overlapping clusters, and at the same time to inform us the degree of membership for each data point in each of the clusters. This not only helps us to grasp the feature of economic fundamentals over the crisis period, but also makes it possible for us to tell the extent to which one or more warning signals were perhaps visible already during the normal development period. As frequently used subjective categories in financial crisis analysis are also often imprecise and do not have sharp boundaries, a fuzzy clustering approach thus seems to provide a simple and natural way to capture hidden patterns relationships in an easier and very flexible way. The preliminary empirical testing shows some interesting results. Nonetheless we would like to point out that the results are only indicative rather than conclusive.

The work presented in this paper will also lay the foundation for our future study on the development of an intelligent agent-based early warning system to support the monitoring and controlling of financial crises. Our immediate next step work will extend along a number of dimensions. First, we will expand the fuzzy clustering analysis to cover a much wider range of financial cases, more countries, longer time periods, and also to include more causal factors (for example country/region specific factors) that should be taken into consideration. Second, we will develop a fuzzy rule system that uses the results from clustering analysis, and will help us to assess the risks of financial crisis in the light of changes in economic fundamentals.

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