China Stock Market Regimes Prediction with Artificial Neural Network and Markov Regime Switching

David Liu, Lei Zhang

***Abstract*—This paper provides an analysis of the Shanghai Stock Exchange Composite Index Movement Forecasting for the period 1999-2009 using two competing non-linear models, univariate Markov Regime Switching model and Artificial Neural Network Model (RBF). The experiment shows that RBF is a useful method for forecasting the regime duration of the Moving Trends of Stock Composite Index. The framework employed also proves useful for forecasting Stock Composite Index turning points. The empirical results in this paper show that ANN method is preferable to Markov-Switching model to some extent.**

***Index Terms*—Artificial neural networks, Nonparametric Estimation, RBF, Regime switching.**

I. Introduction

Many studies conclude that stock returns can be predicted by means of macroeconomic variables with an important business cycle component. Due to the fact that the change in regime should be considered as a random event and not predictable, which could motivate to analyze the Shanghai Stock Exchange Composite Index within this context. There is much empirical support that macroeconomic conditions should affect aggregate equity prices, accordingly, macroeconomic factors would be possibly used for security returns. Merton (1973) and Ross (1976) argued that variables are natural candidates for the common risk factors underlying security returns.

In recent years, Markov Regime Switching models and Neural Networks have been successfully used for modeling financial time series. Markov Regime Switching models seek to capture such discrete shifts in the behavior of financial variables by allowing the parameters of the underlying data-generating process to take on different values in different time periods. Briefly, a framework is established with two states for capturing two different forecasting alternatives. The rationale behind the use of these models stems from the fact that the dynamic changes in Stock Index may be characterized by regime shifts, which means that by allowing the Stock Index to be dependent upon the "state of the market". The ANN methodology is preferred to the alternative non-linear models as it is nonparametric and thus appropriate in estimating any non-linear function without a priori assumptions about the properties of the data.

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In order to study the dynamics of the regime switching of Moving Trends which evolved in the Shanghai Stock Exchange Market, the Composite Index is first modeled in regime switching within a univariate Markov-Switching framework (MRS). One key feature of the MRS model is to estimate the probabilities of a specific state at a time. Past research has developed the econometric methods for estimating parameters in regime-switching models, and demonstrated how regime-switching models can characterize time series behavior of some variables, which is better than the existing single-regime models.

The concept about Markov Switching Regimes firstly dates back to "Microeconomic Theory: A Mathematical Approach" [1]. Hamilton (1989) applied this model to the study of the United States business cycles and regime shifts from positive to negative growth rates in real GNP [2]. Hamilton (1989) extended Markov regime-switching models to the case of auto correlated dependent data. Hamilton and Lin (1996), also report that economic recessions are a main factor in explaining conditionally switching moments of stock market volatility[3-4]. Similar evidences of regime switching in the volatility of stock returns have been found by Hamilton and Susmel (1994), Edwards and Susmel (2001), Coe (2002) and Kanas (2002)[5-8].

Secondly, this paper deals with application of neural network method, a Radial Basis Function (RBF), on the prediction of the moving trends of the Shanghai Stock. RBFs have been employed in time series prediction with success as they can be trained to find complex relationships in the data (Chen, Cowan and Grant. 1991) [9].

A large number of successful applications have shown that ANN models have received considerable attention as a useful vehicle for forecasting financial variables and for time-series modeling and forecasting (Swanson and White, 1995, Zhang, Patuwo and Hu, 1998) [10-11]. In the early days, these studies focused on estimating the level of the return on stock price index. Current studies reflect an interest in selecting the predictive factors as a variety of input variables to forecast stock returns by applying neural networks. Several techniques such as regression coefficients (Kimoto et al. 1990, Qi and Maddala, 1999), autocorrelations (Desai and Bharati, 1998), backward stepwise regression (Motiwalla and Wahab, 2000), and genetic algorithms (Motiwalla and Wahab, 2000, Kim and Han, ect 2002) have been employed by researchers to perform variable subset selection [12-13]. In addition, several researchers (Leung et al. (2000), Gencay (1998), and Pantazopoulos et al. (1998)), subjectively selected the subsets of variables based on empirical evaluations [14].

The objective of this paper is not only to examine the feasibility of the two non-linear models but present an effort on improving the accuracy of RBF in terms of data pre-processing and parameter selection. Both non-linear models are able to find non-linear relationships in 'real-world' financial series. Especially, the ANN method performs better on the duration prediction compared to the non-linear Markov-Switching model.

The paper is organized as follows. Section 2 is Data Description and Preliminary Statistics. Section 3 presents the research methodology. Section 4 presents and discusses the empirical results. The final section provides with summary and conclusion.

II. DATA DESCRIPTION AND PRELIMINARY STATISTICS

A. Data Description

This paper adopts two non-linear models, Univariate Markov Switching model and Artificial Neural Network Model with respect to the behavior of Chinese Stock Exchange Composite Index using data for the period from 1999 to 2009. As the Shanghai Stock Exchange is the primary stock market in China and Shanghai A Share Composite is the main index reflection of Chinese Stock Market, this research adopts the Shanghai Composite (A Share). The data consist of daily observations of the Shanghai Stock Exchange Market general price index for the period 29 October 1999 to 31 August 2009, excluding all weekends and holidays giving a total of 2369 observations. For both the MRS and the ANN models, the series are taken in natural logarithms.

B. Preliminary Statistics

In this part we will explore the relationship among Shanghai Composite and Consumer Price Index, Retail Price Index, Corporate Goods Price Index, Social Retail Goods Index, Money Supply, Consumer Confidence Index, Stock Trading by using various t-tests, and regression analysis to pick out the most relevant variables as the influence factors in our research.

By using regression analysis we test the hypothesis and identify correlations between the variables. In the following multiple regression analysis we will test the following hypothesis and see whether they hold true:

$H_0 = \beta_1 = \beta_2 = \beta_3 = \ldots = \beta_K = 0$

$H_1 =$ At least some of the β is not equal 0 (regression insignificant)

In Table 1, R-Square (R^2) is the proportion of variance in the dependent variable (Shanghai Composite Index) which can be predicted from the independent variables. This value indicates that 80% of the variance in Shanghai Composite Index can be predicted from the variables Consumer Price Index, Retail Price Index, Corporate Goods Price Index, Social Retail Goods Index, Money Supply, Consumer Confidence Index, and Stock Trading. It is worth pointing out that this is an overall measure of the strength of association, and does not reflect the extent to which any particular independent variable is associated with the dependent variable.

In Table 2, the p-value is compared to alpha level (typically 0.05). This gives the F-test which is significant as p-value =0.000. This means that we reject the null that Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index, Money Supply have no effect on Shanghai Composite.

We could say that the group of variables awareness, intention, preference and attitude can be used to reliably predict loyalty (the dependent variable). The p=value (Sig.) from the F-test in ANOVA table is 0.000, which is less than 0.001 implying that we reject the null hypothesis that the regression coefficients (β's) are all simultaneously correlated.

By looking at the Sig. column in particular, we gather that Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index, Money Supply are variables with p-values less than .02 and hence VERY significant.

Then look at Fig.1 and Fig. 2, the correlation numbers measure the strength and direction of the linear relationship between the dependent and independent variables. In the scatterplots we show the plot of observed cum prob and the expected cum prob. To show these correlations visually we use partial regression plots. Correlation points tend to form along a line going from the bottom left to the upper right, which is the same as saying that the correlation is positive. We conclude that Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index, Money Supply and their correlation with Shanghai Composite Index is positive because the points tend to form along this line.

Due to CPI Index, CGPI Index and Money Supply Increased Ratio (M1 Increased Ratio –M2 Increased Ratio) are the most correlated influence factors with Share Composite among other factors. Therefore, we choose macroeconomic indicators as mentioned by Qi and Maddala (1999), CPI Index, CGPI Index and Money Supply Increased Ratio (M1 Increased Ratio –M2 Increased Ratio) as well as a data set from Shanghai Stock Exchange Market are used for the experiments to test the forecasting accuracy of RBF [12]. Typically, Fig.3 and Fig.4 show the developments of Shanghai Composite index with CPI, CGPI and MS along time.

III. EMPIRICAL MODELS

In this section, the univariate Markov Switching Model developed by Hamilton (1989) was adopted to explore regime switching of the Shanghai Stock Exchange Composite Index, followed by developing an artificial neural network (ANN) – a RBF method to predict stock index moving trends. We use the RBF method to find the relationship of CPI Index, CGPI Index and Money Supply Increased Ratio with Stock Composite Index. Using the Matlab Neural Network Toolbox, RBF Network is designed in a more efficient design (newrb). Finally, the forecasting performances of these two competing non-linear models are compared.

A. Markov Regime Switching Model and Estimation

Markov Regime Switching Model

The comparison of the in sample forecasts is done on the basis of the Markov Switching/Hamilton filter mathematical notation, using the Marcelo Perlin (21 June 2009 updated) forecasting modeling.

A potentially useful approach to model nonlinearities in time series is to assume different behavior (structural break) in one subsample (or regime) to another. If the dates of the regimes switches are known, modeling can be worked out with dummy variables. For example, consider the following regression model: $y_t = X_t' \beta_{S_t} + \varepsilon_t$ (t=1, ... T,) (1)

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Where, $\varepsilon_t \sim \text{NID}\,(0, \sigma^2{}_{S_t})$, $\beta_{S_t} = \beta_0(1 - S_t) + \beta_1 S_t$
$\sigma^2{}_{S_t} = \sigma^2{}_0(1 - S_t) + \sigma^2{}_1 S_t$, $S_t = 0$ or 1, (Regime 0 or 1).

Usually it is assumed that the possible difference between the regimes is a mean and volatility shift, but no autoregressive change. That is:

$$y_t = \mu_t S_t + \emptyset(y_{t-1} - \mu_{S_{t-1}}) + \epsilon_t\,, \qquad (2)$$

$\epsilon_t \sim \text{NID}\,(0, \sigma^2{}_{S_t})$

Where, $\mu_t S_t = \mu_0(1 - S_t) + \mu_1 S_t$, if S_t (t=1, ..., T) is known a priori, then the problem is just a usual dummy variable autoregression problem.

In practice, however, the prevailing regime is not usually directly observable. Denote then P $(S_t = j|S_{t-1} = i) = P_{ij}$, (i, j $= 0,\ 1$), called transition probabilities, with $P_{i0} + P_{i1} = 1$, $i = 0,\ 1$. This kind of process, where the current state depends only on the state before, is called a Markov process, and the model a Markov switching model in the mean and the variance. The probabilities in a Markov process can be conveniently presented in matrix form:

$$\begin{pmatrix} P(S_t = 0) \\ P(S_t = 1) \end{pmatrix} = \begin{pmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{pmatrix} \begin{pmatrix} P(S_{t-1} = 0) \\ P(S_{t-1} = 1) \end{pmatrix}$$

Estimation of the transition probabilities P_{ij} is usually done (numerically) by maximum likelihood as follows. The conditional probability densities function for the observations y_t given the state variables, S_{t-1} and the previous observations $F_{t-1} = \{y_{t-1}\,,\ y_{t-2}\,,\ \ldots\}$ is

$$f\,(y_t|S_t, S_{t-1}, F_{t-1}\,) = \frac{1}{\sqrt{2\pi\sigma^2_{S_t}}} \exp\left[-\frac{[y_t - \mu_t S_t - \emptyset(y_{t-1} - \mu_{S_{t-1}})]^2}{2\sigma^2_{S_t}}\right] \qquad (3)$$

$$\epsilon_t = y_t - \mu_t S_t - \emptyset(y_{t-1} - \mu_{S_{t-1}}) \sim \text{NID}\,(0, \sigma^2{}_{S_t}).$$

The chain rule for conditional probabilities yields then for the joint probability density function for the variables $y_t\,, S_t, S_{t-1}$, given past information F_{t-1} . $f(y_t, S_t\,, S_{t-1}|\,F_{t-1}\,) = f(y_t\,|S_t\,, S_{t-1}\,, F_{t-1}\,)P(S_t\,, S_{t-1}\ |F_{t-1}\,)$, such that the log-likelihood function to be maximized with respect to the unknown parameters becomes $l_t(\theta) = \log\left[\sum_{S_t=0}^{1} \sum_{S_{t-1}=0}^{1} f\,(y_t\,|S_t, S_{t-1}\,, F_{t-1}\,)\ P(S_t, S_{t-1}\ |F_{t-1})\right]$

$$\theta = (p, q, \emptyset, \mu_0, \mu_1, \sigma_0^2, \sigma_1^2) \qquad (4)$$

and the transition probabilities:
$p = P(S_t = 0|S_{t-1} = 0)$, and $q = P(S_t = 1|S_{t-1} = 1)$. Steady state probabilities $P(S_0 = 1/F_0\,)$ and $P(S_0 = 0/F_0)$ are called the steady state probabilities, and, given the transition probabilities p and q, are obtained as:
$P(S_0 = 1/F_0) = \frac{1-p}{2-q-p}$, $P(S_0 = 0/F_0) = \frac{1-q}{2-q-p}$.

Stock Composite Index Moving Trends Estimation

In our case, we have 3 explanatory variables X_{1t},X_{2t}, X_{3t} in a Gaussian framework (Normal distribution) and the input argument S, which is equal to S= [1 1 1 1], then the model for the mean equation is:

$$y_t = X_{1t}\beta_{1,S_t} + X_{2t}\beta_{2,S_t} + X_{3t}\beta_{3,S_t} + \varepsilon_t \qquad (5)$$
$$(\varepsilon_t \sim \text{NID}\,(0, \sigma^2{}_{S_t}))$$

Where, S_t represent the state at time t, that is, $S_t = 1\ldots K$, (K is the number of states); $\sigma^2{}_{S_t}$- Error variance at state S_t; β_{S_t}- beta coefficient for explanatory variable i at state S_t , where i goes from 1 to n; ε_t- residual vector which follows a particular distribution (in this case Normal).

With this change in the input argument S, the coefficients and the model's variance are switching according to the transition probabilities. Therefore, the logic is clear: the first elements of input argument S control the switching dynamic of the mean equation, while the last terms control the switching dynamic of the residual vector, including distribution parameters.

Based on Gaussian maximum likelihood, the equations are represented as following:

State 1 (=1)
$$y_t = X_{1t}\beta_{1,1} + X_{2t}\beta_{2,1} + X_{3t}\beta_{3,1} + \varepsilon_t$$
State 2 (=2)
$$y_t = X_{1t}\beta_{1,2} + X_{2t}\beta_{2,2} + X_{3t}\beta_{3,2} + \varepsilon_t$$
With:
$$\begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}$$
as the transition matrix, which controls the probability of a regime switch from state j (column j) to state i (row i). The sum of each column in P is equal to one, since they represent full probabilities of the process for each state.

B. Radial Basis Function neural networks

An ANN model represents an attempt to estimate certain features of the way in which the brain processes information. The specific type of ANN employed in this study is the Radial Basis Function (RBF), the most widely used of the many types of neural networks. RBFs were first used to solve the interpolation problem-fitting a curve exactly through a set of points (Powell, 1987).

Fausett defines radial basis functions as "activation functions with a local field of response at the output (Fausett, 1994)" [15]. The RBF neural networks are trained to generate both time series forecasts and certainty factors.

The RBF neural network is composed of three layers of nodes (Fig.5). The first is the input layer that feeds the input data to each of the nodes in the second or hidden layer. The second layer of nodes differs greatly from other neural networks in that each node represents a data cluster which is centered at a particular point and has a given radius. The third and final layer consists of only one node. It acts to sum the outputs of the second layer of nodes to yield the decision value (Moody and Darken, 1989) [16].

The ith neurons input of a hidden layer is: $k_i^q = \sqrt{\sum_j \left(W1_{ji} - X_j^q\right)^2} \times bl_i$ and output is:

$$r_i^q = \exp\left(-\left(k_i^q\right)^2\right) = \exp\left(\sqrt{\sum_j \left(W1_{ji} - X_j^q\right)^2} \times b1_i\right)$$
$$= \exp\left(-\left(\left\|W1_i - X_j^q\right\| \times b1_i\right)^2\right)$$

Where $b1_i$ resents threshold value, X_j is the input feature vector and the approximant output r_i^q is differentiable with respect to the weights $W1_i$.

When an input vector is fed into each node of the hidden layer simultaneously, each node then calculates the distance from the input vector to its own center. That distance value is transformed via some function, and the result is output from the node. That value output from the hidden layer node is multiplied by a constant or weighting value. That product is fed into the third layer node which sums all the products and any numeric constant inputs. Lastly, the third layer node outputs the decision value (Fig. 6).

A Gaussian basis function for the hidden units given as Z_j for j=1, 2, … J, where

$$Z_j = \exp\left(\frac{-\left\|X - \mu_j\right\|^2}{2\sigma^2}\right)$$

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μ_j and σ_j are mean and the standard deviation respectively, of the jth unit receptive field and the norm is Euclidean.

Networks of this type can generate any real-valued output, but in our applications where we have a priori knowledge of the range of the desired outputs, it is computationally more efficient to apply some nonlinear transfer function to the outputs to reflect that knowledge.

In order to obtain the tendency of A Share Composite Index, we examine the sample performance of quarterly returns (totally 40 quarters) forecasts for the Shanghai Stock Exchange Market from October 1999 to August 2009, using three exogenous macroeconomic variables, the CPI, CGPI and Money Supply (M1-M2, Increased on annual basis) as the inputs to the model. We use a Radial Basis Function network based on the learning algorithm presented above. Using the Matlab Neural Network Toolbox, the RBF network is created using an efficient design (newrb). According to Hagan, Demuth and Beale (1996), a small spread constant can result in a steep radial basis curve while a large spread constant results in a smooth radial basis curve [17]; therefore it is better to force a small number of neurons to respond to an input. Our interest goes to obtain a single consensus forecast output, the sign of the prediction only, which will be compared to the real sign of the prediction variable. After several tests and changes to the spread, at last we find spread=4 is quite satisfied for out test. As a good starting value for the spread constant is between 2 and 8 (Hagan Demuth and Beale, 1996), we set the first nine columns of y' as the test samples [17].

IV. Empirical Results

A. *Stock Composite Index Moving Trends Estimation by MRS*

Table 3 shows the estimated coefficients of the proposed MRS along with the necessary test statistics for evaluation of Stock Composite Index Moving Trends. The Likelihood Ratio test for the null hypothesis of linearity is statistically significant and this suggests that linearity is strongly rejected. The results in Table 3 further highlight several other points: First, value of the switching variable at state 1 is 0.7506, at state 2 value of the switching variable is -0.0161; secondly, the model's standard deviation σ takes the values of 0.0893 and 0.0688 for regime 1 and regime 2 respectively; these values help us to identify regime 1 as the upward regime and regime 2 as the downward regime. Second, the duration measure shows that the upward regime lasts approximately 57 months, whereas the high volatility regime lasts approximately 24 months.

As we use the quarterly data for estimating the Moving Trends, the smoothed probabilities and filtered state probabilities lines seem exiguous. Fig.7 reveals the resulting smoothed probabilities of being in up and down moving trends regimes along the Shanghai Stock Exchange Market general price index. Moreover, filtered States Probabilities was shown in Fig.8, several periods of the sample are characterized by moving downwards associated with the presence of a rational bubble in the capital market of China from 1999 to 2009.

B. *Radial Basis Function neural networks*

Interestingly, the best results we obtained from RBF training are 100% correct approximations of the sign of the test set, and 90% of the series on the training set. This conclusion on one hand is consensus with the discovery by Hamilton and Lin (1996) the Stock Market and the Business Cycle. Hamilton and Lin (1996) argued that the analysis of macroeconomic fundamentals is certainly a satisfactory explanation for stock volatility. To our best knowledge, the fluctuations in the level of macroeconomic variables such as CPI and CGPI and other economic activity are a key determinant of the level of stock returns. On the other hand, in a related application, Girosi and Poggio (1990) also show that RBFs have the "best" approximation property-there is always a choice for the parameters that is better than any other possible choice-a property that is not shared by MLPs[18].

Due to the Normal Distributions intervals, we classify the outputs by the following forms:

$$y' = F(x) = \begin{cases} F(x) = 1 & \text{if } x \geq 0.5 \\ F(x) = 0 & \text{if } x < 0.5 \end{cases}$$

Table 4 gives the results of the outputs. From x we could know that the duration of regime 1 is 24 quarters and regime 0 is 16 quarters. The comparisons of MRS and RBF models could be seen in Table 5. It is clear that the RBF model outperforms the MRS model on the regime duration estimation.

V. Conclusion

In this article, we compare the forecasting performance of two nonlinear models to address issues with respect to the behaviors of aggregate stock returns of Chinese Stock Market. Rigorous comparisons between the two nonlinear estimation methods have been made. From the Markov-Regime Switching model, it can be concluded that real output growth is subject to abrupt changes in the mean associated with economy states. On the other hand, the ANN method developed with the prediction algorithm to obtain abnormal stock returns, indicates that stock returns should take into account the level of the influence generated by macroeconomic variables. Further study will concentrate on prediction of market volatility using this research framework.

Appendix

Table 1 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.653[a]	.427	.422	768.26969
2	.773[b]	.597	.590	647.06456
3	.834[c]	.695	.688	564.83973
4	.873[d]	.763	.755	500.42457
5	.894[e]	.800	.791	461.69574

a. Predictors: (Constant), Stock Trading

b. Predictors: (Constant), Stock Trading, Consumer Price Index

c. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index

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d. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index

e. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index, Money Supply

f. Dependent Variable: Shanghai Composite

Table 2 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.323E7	1	5.323E7	90.178	.000[a]
	Residual	7.142E7	121	590238.317		
	Total	1.246E8	122			
2	Regression	7.440E7	2	3.720E7	88.851	.000[b]
	Residual	5.024E7	120	418692.539		
	Total	1.246E8	122			
3	Regression	8.668E7	3	2.889E7	90.561	.000[c]
	Residual	3.797E7	119	319043.922		
	Total	1.246E8	122			
4	Regression	9.510E7	4	2.377E7	94.934	.000[d]
	Residual	2.955E7	118	250424.748		
	Total	1.246E8	122			
5	Regression	9.971E7	5	1.994E7	93.549	.000[e]
	Residual	2.494E7	117	213162.957		
	Total	1.246E8	122			

a. Predictors: (Constant), Stock Trading

b. Predictors: (Constant), Stock Trading, Consumer Price Index

c. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index

d. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index

e. Predictors: (Constant), Stock Trading, Consumer Price Index, Consumer Confidence Index, Corporate Goods Price Index, Money Supply

f. Dependent Variable: Shanghai Composite

Table 3 Stock Index Moving Trends Estimation by MRS

Parameters	Estimate	Std err
μ_0	0.7506	0.0866
μ_1	-0.0161	0.0627
σ_0^2	0.0893	0.0078
σ_1^2	0.0688	0.0076
Expected duration	56.98 time periods	23.58 time periods
Transition Probabilities		
p(regime1)	0.98	
q(regime0)	0.96	
Final log Likelihood	119.9846	

Distribution Assumption -> Normal

Table 4 RBF Training Output

x	y'	T	x	y'	T
0.80937	1	1	0.031984	0	0
0.30922	0	0	0.80774	1	0
0.96807	1	1	0.68064	1	0
1.0459	1	1	0.74969	1	0
-0.011928	0	0	0.54251	1	1
0.92	1	1	0.91874	1	1
0.81828	1	1	0.50662	1	1
0.054912	0	0	0.44189	0	1
0.34783	0	0	0.59748	1	1
0.80987	1	1	0.69514	1	1
1.1605	1	1	1.0795	1	1
0.66608	1	1	0.16416	0	0
0.22703	0	0	0.97289	1	1
0.45323	0	0	-0.1197	0	0
0.69459	1	1	0.028258	0	0
0.16862	0	0	0.087562	0	0
0.83891	1	1	-0.084324	0	0
0.61556	1	1	1.0243	1	1
1.0808	1	1	0.98467	1	1
-0.089779	0	0	0.0032105	0	0

Table 5 Regime Comparison of Stock Index Moving Trends

Model	Regime 1	Regime 0
Observed Durations	66 months	54 months
Markov-Switching	57 months	24 months
Radial Basis Function	72 months	48 months

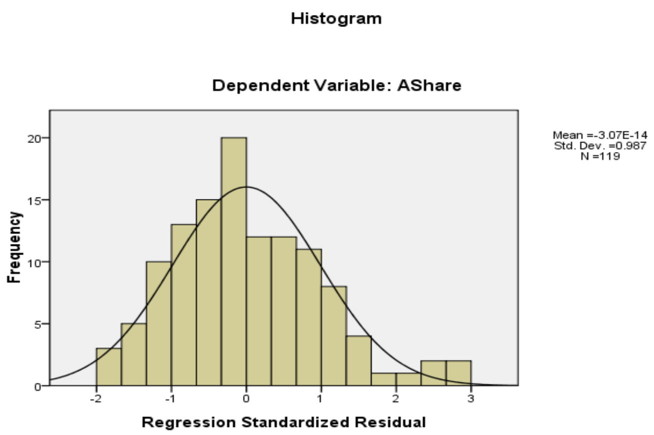

Fig.1: Frequency against Regression Residual

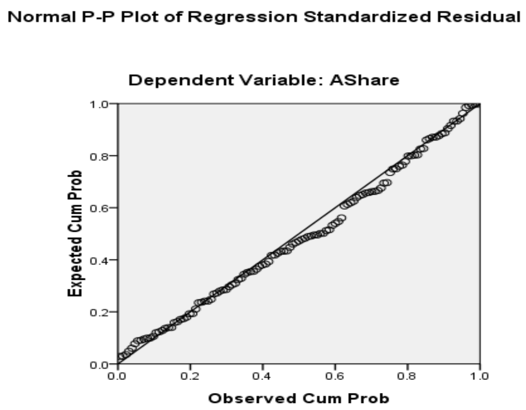

Fig.2: Normal P-P Plot Regression Standardized Residual

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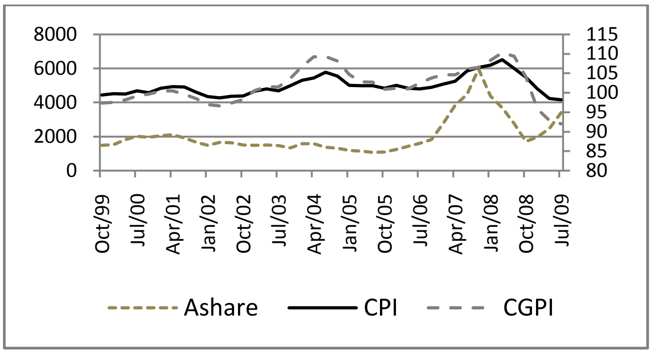

Fig.3: China CPI, CGPI and Shanghai A Share Composite Index

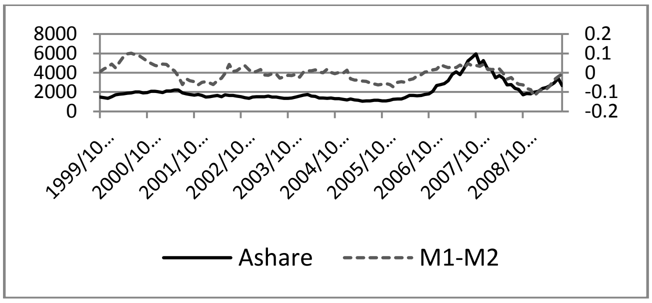

Fig.4: China Money Supply Increased (annual basis) and Shanghai A Share Composite Index Ratio

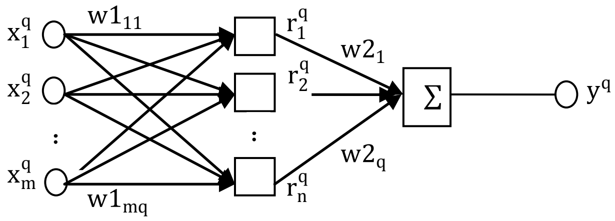

Fig.5: RBF Network Architecture

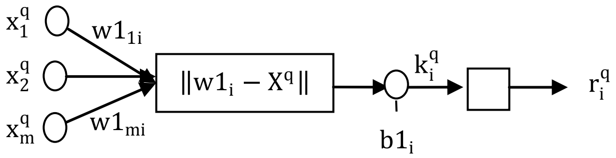

Fig.6: RBF network hidden layer neurons input and output

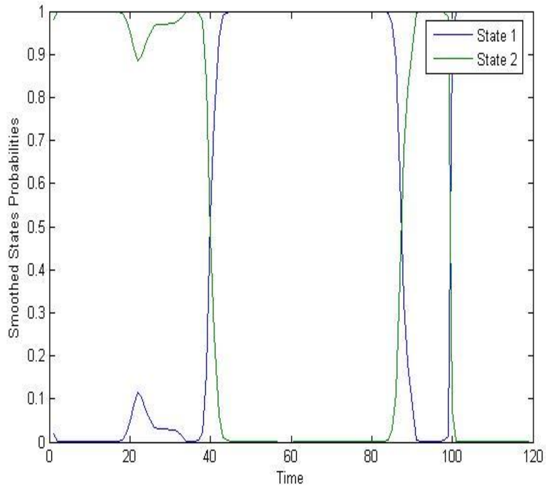

Fig.7: Smoothed States Probabilities (Moving Trends)

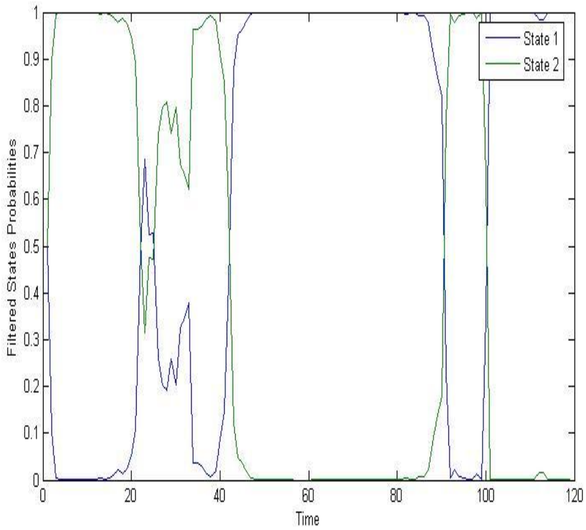

Fig. 8: Filtered States Probabilities (Moving Trends)

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