APPLICATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM IN INTEREST RATES EFFECTS ON STOCK RETURNS

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Abstract

In the current study we examine the effects of interest rate changes on common stock returns of Greek banking sector. We examine the Generalized Autoregressive Heteroskedasticity (GARCH) process and an Adaptive Neuro-Fuzzy Inference System (ANFIS). The conclusions of our findings are that the changes of interest rates, based on GARCH model, are insignificant on common stock returns during the period we examine. On the other hand, with ANFIS we can get the rules and in each case we can have positive or negative effects depending on the conditions and the firing rules of inputs, which information is not possible to be retrieved with the traditional econometric modelling. Furthermore we examine the forecasting performance of both models and we conclude that ANFIS outperforms GARCH model in both in-sample and out-of-sample periods.

Keywords: ANFIS, Interest rates, Stock returns

1. Introduction

The issue of interest rate sensitivity remains empirically unresolved. Most of the studies use a variety of short-term and long-term bond returns as the interest rate factor without providing any rationale for their use. Yet, there is no consensus on the choice of the interest rate factor that should be used in testing the two-factor model. There is a broad consensus among the practitioners and academics that interest rates have a significant effect on share prices, but also there is a little agreement as to whether or not interest rates affect the stock returns. The problem with econometrics is that are based on probabilities and statistics and not on possibilities and membership. To be specific it impossible to find insignificant estimated coefficients over a specific period we examine and therefore we conclude that the phenomenon we examine is rejected, in our cases the effects of interest rates changes on stock returns. This is not absolute logical and correct because traditional econometrics are not able to capture imprecision and non linearities. With fuzzy logic we can retrieve the rules when a specific condition is fired, so there will be always positive and negative effects, in our case, based on specific rules and behaviour of inputs. For example with conventional econometric modelling we can find that there are not significant effects in a specific period, but there are in a sub-period. And the question is how can we find this period? Even if we apply rolling regressions this is not very helpful for financial practical purposes.

Additionally, conventional econometric modelling is based on statistical properties, where a long sample is needed. Also, misspecification errors, heteroskedasticity, ARCH effects and autocorrelation in residuals are some problems of econometric estimations. With fuzzy logic and neural networks we can take all the inputs and examine their importance weight in the determination of the output with short or long sample as long as fuzzy rules have been defined. Furthermore, neuro-fuzzy modelling, because it is not based on statistical and econometric properties, autocorrelation and heteroskedasticity in residuals, among other problems, are not examined as the disturbance term is not included in fuzzy regressions and neuro-fuzzy system therefore these problems have no meaning. A proposal for further research study and applications is to introduce the disturbance term in fuzzy and neuro-fuzzy modelling. Additionally, neural networks have been criticized that are black boxes but are able to describe very well the nonlinearities. On the other hand fuzzy logic is not always able to describe nonlinearities appropriately, but is the most efficient method to approach imprecision, and especially in finance, because is determined by human behaviour and this is exactly the true imprecision. More specifically, econometric methodology treats human behavior as a computer based on binary logic with only two possible values, true or false, yes or no, expansive or recessive. To be correct the real values that a human expresses are maybe true, maybe false, or true if and false if. For this reason we use Neuro-Fuzzy system and we believe that is the future in economics and econometrics, as artificial intelligence procedures are already used in finance.

The structure of the paper has as follows: In section 2 we present a short literature review, in section 3 we present the methodology for the GARCH process and the two-index factor model, as also the methodology of ANFIS is described. In section 4 we present the period examined and we describe the data frequency, while in section 5 we present the empirical results and we discuss about them. Finally, in the final section we report our concluding remarks of our findings.

2. Literature Review

There is a great number of research studies examining the effects of interest rate changes on stock prices and not returns. Fama [1981] documents a strong positive correlation between common stock returns and real economic variables like capital expenditures, industrial production, real GNP, money supply, lagged inflation and interest rates. Hardouvelis [1987] points out that an inverse relationship between stock prices and changes of interest rate exists and this can be rationalized in terms of money supply surprises. Chen *et al.* [1999] examine the effect of discount rate changes on the volatility of stock prices and on trading volume and they found that unexpected discount rate changes contributed to higher, though short-lived, volatility and trading volume.

Stock returns sensitivity to interest rates was theoretically advocated by Merton [1973], Long [1974] and Stone [1974]. Essentially, risk averse investors demand higher compensation for exposure to factors, other than the market portfolio, that are correlated with intertemporal changes in the investment opportunity set. Stone [1974] has offered another means of expanding the market model. He has proposed a two-index model consisting of the traditional equity market index and a debt market index and he justified the model by arguing that individual equity securities exhibit varying degrees of sensitivity to interest rates and that the opportunity to invest in risky debt securities may represent an attractive alternative to riskless assets and risky equity securities. Booth and Officer [1985] and Bae [1990] test the effect of current and unanticipated changes in interest rate. Fraser *et al.,* [2002[examine the effect of unanticipated rate changes. All these studies, as also other research empirical evidences [Fama and Schwert (1977); Christie, (1981)], found strong support for a negative effect of both current and unanticipated interest changes on bank stock returns. While some studies have found the interest rate factor to be an important determinant of common stock returns of banks, on the contrast Chance and Lane [1980] have found the returns to be insensitive or other supporting that stock returns only marginally explained by the interest rate factor, so these studies find no incremental explanatory power for interest rate changes [Lloyd and Shick, 1977)]. Research studies employing fuzzy logic, ANFIS and generally artificial intelligence procedures have not yet been made.

3. Methodology

3.1 *Two factor model*

The proposed generalized formulation of the two-factor model [Stone, (1974)] is as follows:

$$R_{pit} = \beta_{i0} + \beta_{i1}R_{mt} + \beta_{i2}\Delta I_t + \varepsilon_{it} \tag{1}$$

, where

β_{i0} is the constant

R_{pit} denotes the weekly returns of an equally weighted portfolio *i* of stock in week *t,*

R_{mt} is the weekly return on the market portfolio in week *t,*

ΔI_t is a default free debt index as proxy of interest rates in period *t,*

ε_{it} is a stationary y stochastic process with zero mean for each portfolio *i,*

The one month , three, six and twelve months Treasury bill rates have been tested as the interest rate variable in equation (1), but we present randomly only the results for three months Treasury bill rates because the conclusions are the same in all cases and there is no difference using short-term or longer-term interest rates. Because with ordinary least squares we found autocorrelation and ARCH effects we estimate with symmetric GARCH (p,q) process, which is mainly used in financial econometric literature. GARCH model was proposed by Bollerslev [1986]. The mean equation remains the same as in equation (1) but GARCH (1,1) process is:

$$\varepsilon_{it} \sim (0, \sigma_{,t}^2) \tag{2}$$

, where

$$\sigma_{,t}^2 = \gamma_0 + \gamma_1 u_{,t-1}^2 + \gamma_2 \sigma_{t-1}^2 \tag{3}$$

Additionally we have tested asymmetric GARCH models [Nelson, (1991); Glosten *et al*., (1993)] but the results are not presented, as are exactly the same with those of symmetric GARCH process.

3.2 Adaptive Neuro-Fuzzy Iinference System (ANFIS)

We follow a simple ANFIS system in order to improve its forecasting performance and to make it much more useful. We incorporate two linguistic terms {positive, negative}. More linguistic terms can be introduced, as very positive and very negative, but the forecasting performance is almost the same, indicating that we can simplify the procedure by taking less linguistic terms and less rules. On the other hand more linguistic terms might be more useful, but in the case we examine financial professionals and traders are interesting mainly on positive and negative returns. The rules are 4 because we have two inputs with two linguistic terms and it is 2*2=4. These rules are:

IF *RET is negative AND IR is negative THEN* $f_1 = p_1 x_1 + q_1 x_2 + r_1$

IF *RET is negative AND IR is positive THEN* $f_2 = p_2 x_1 + q_2 x_2 + r_2$

IF *RET is positive AND IR is negative THEN* $f_3 = p_3 x_1 + q_3 x_2 + r_3$

IF *RET is positive AND IR is positive THEN* $f_4 = p_4 x_1 + q_4 x_2 + r_4$

, where *RET* denotes the General stock index returns and *IR* denotes the interest rate changes. We choose the *AND* operator so we will take the *product* instead to *min* operator to avoid monotonic results. Also each rule has 2 parameters plus the constant hence there will be 3*4=12 parameters.

Jang [1993] and Jang and Sun [1995] introduced the adaptive network-based fuzzy inference system (ANFIS). This system makes use of a hybrid learning rule to optimize the fuzzy system parameters of a first order Sugeno system. An example of a two input with two rules first order Sugeno system can be graphically represented by Fig. 1.
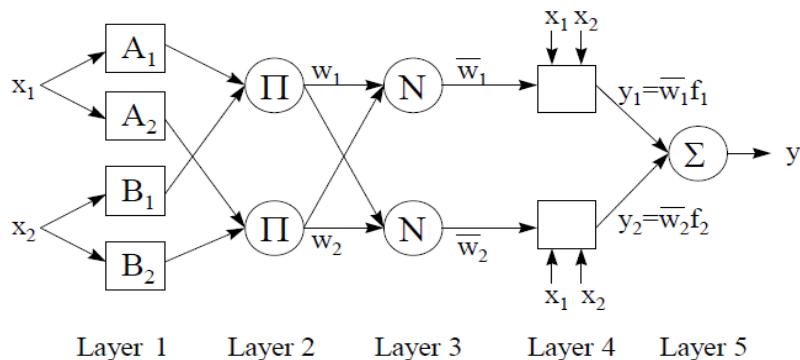

Fig. 1 Example of ANFIS architecture for a two-input, two-rule first-order Sugeno model

, where the consequence parameters *p*, *q*, and *r* of the nth rule contribute through a first order polynomial of the form:

$$f_n = p_n x_1 + q_n x_2 + r_n \tag{4}$$

The ANFIS architecture is consisted of two trainable parameter sets, the antecedent membership function parameters and the polynomial consequent parameters *p,q,r*. The ANFIS training paradigm uses a gradient descent algorithm to optimize the antecedent parameters and a least squares algorithm to solve for the consequent parameters. Because it uses two very different algorithms to reduce the error, the training rule is called a hybrid. The consequent parameters are updated first using a least squares algorithm and the antecedent parameters are then updated by backpropagating the errors that still exist. The ANFIS architecture consists of five layers with the output of the nodes in each respective layer represented by O_i^l, where *i* is the ith node of layer l. Because we have four rules and two inputs in the case we examine the steps for ANFIS system computation are:

In the first layer we generate the membership grades

$$O_i^1 = \mu_{A_i}(x_1), \mu_{B_i}(x_2) \tag{5}$$

, where x_1 and x_2 are the inputs. In layer 2 we generate the firing strengths or weights

$$O_i^2 = w_i = \prod_{j=1}^{m} (\mu_{A_i}(x_1), \mu_{B_i}(x_2)) = andmethod\,(\mu_{A_i}(x_1), \mu_{B_i}(x_2))$$
$$= product\,(\mu_{A_i}(x_1) \cdot \mu_{B_i}(x_2)) \tag{6}$$

In layer 2 we use the *AND* relation, as it was mentioned previously, so we take the *product* operator. In layer 3 we normalize the firing strengths and it will be:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2 + w_3 + w_4} \tag{7}$$

, where *i* is for *i=1,2,3,4*. In layer 4 we calculate rule outputs based on the consequent parameters.

$$O_i^4 = y_i = \overline{w_i} f_i = \overline{w_i}(p_i x_1 + q_i x_2 + r_i) \tag{8}$$

In layer 5 we take

$$O_i^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i \overline{w_i} f}{\sum_i \overline{w_i}} \tag{9}$$

In the last layer the consequent parameters can be solved for using a least square algorithm as:

$$Y = X \cdot \theta \tag{10}$$

, where X is the matrix

$$X = [w_1 x + w_1 + w_2 x + w_2 + ... + w_9 x + w_9] \tag{11}$$

and θ is a vector of unknown parameters as:

$$\theta = [p_1, q_1, r_1, p_2, q_2, r_2, ,..., p_9, q_9, r_9]^T \tag{12}$$

, where *T* indicates the transpose. Because the normal least square method leads to singular inverted matrix we use the Singular Value Decomposition (SVD) with Moore-Penrose pseudoinverse of matrix [Moore, (1920); Penrose, (1955); Petrou and Bosdogianni, (2000)]. Other methods that can be used to eliminate the particular problem is Lower Triangular, Upper Triangular and Orthogonal decomposition (QR) among others. More specifically the Singular Value Decomposition (SVD) procedure is:

$$X = USV^T \tag{13}$$

The singular values in S are positive and arranged in decreasing order. Their magnitude is related to the information content of the columns of U -principle components- that span X. Therefore, to remove the noise effects on the solution of the weight matrix, we simply remove the columns of U that correspond to small diagonal values in S. The weight matrix is then solved for using the following:

$$\theta = VS^{-1}U^{T}Y \tag{14}$$

For the first layer and relation (5) we use the Triangular, Gaussian and sigmoidal shape membership functions. We have described the computation procedure for the consequent parameters by using least squares algorithm with Moore-Penrose pseudoinverse matrix. The next step is to describe the training procedure for the antecedent parameters with the error backpropagation algorithm and the simple steepest descent method [Tsoukalas and Uhrig, (1996); Denai et al., (2004); Khan et al., (2010)]. The triangular function is defined as:

$$\mu_{ij}(x_j; a_{ij}, b_{ij}) = \begin{cases} 1 - \dfrac{|x_j - a_{ij}|}{b_{ij}/2}, & if \ |x_j - a_{ij}| \le \dfrac{b_{ij}}{2} \\ 0, & otherwise \end{cases} \tag{15}$$

, where a_{ij} is the peak or center parameter and b_{ij} is the spread or support parameter. The symmetrical Gaussian membership function is defined as:

$$\mu_{ij}(x_j; c_{ij}, \sigma_{ij}) = \exp\left(-\frac{(x_j - c_{ij})^2}{2\sigma_{ij}^2}\right) \tag{16}$$

, where c_{ij} is the center parameter and σ_{ij} is the spread parameter. The last membership function we examine is the Sigmoid shape function such as:

$$\mu_{ij}(x_j; a_{ij}, c_{ij}) = \frac{1}{1 + \exp(-a_{ij}(x_{ij} - c_{ij}))} \tag{17}$$

, where c_{ij} locates the center of the curve and a_{ij} is the spread parameter. The antecedent parameter c update is:

$$c_{ij}(n+1) = c_{ij}(n) - \frac{\eta_c}{p} \cdot \frac{\partial E}{\partial c_{ij}} \tag{18}$$

,where η_c is the learning rate for the parameter c_{ij}, p is the number of patterns and E is the error function which is:

$$E = \frac{1}{2}(y - y^t)^2 \tag{19}$$

, where y^t is the target-actual and y is ANFIS output variable. The chain rule in order to calculate the derivatives used to update the membership function parameters are:

$$\frac{\partial E}{\partial c_{ij}} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial y_i} \cdot \frac{\partial y_i}{\partial w_i} \cdot \frac{\partial w_i}{\partial \mu_{ij}} \frac{\partial \mu_{ij}}{\partial c_{ij}} \tag{20}$$

The partial derivatives for two inputs are derived below:

$$\frac{\partial E}{\partial y_{ij}} = y - y^t = e \tag{21}$$

For the output is:

$$y = \sum_{i=1}^{n} y_i \tag{22}$$

, hence it will be

$$\frac{\partial y}{\partial y_i} = 1 \tag{23}$$

$$y_i = \frac{w_i}{\sum\limits_{i=1}^{n} w_i}(p_i x_1 + q_i x_2 + r_i) \tag{24}$$

, hence it will be :

$$\frac{\partial y_i}{\partial w_i} = \frac{(p_i x_1 + q_i x_2 + r_i) - y}{\sum\limits_{i=1}^{n} w_i} \tag{25}$$

$$w_i = \prod\limits_{j=1}^{m} \mu_{A_{ji}} \tag{26}$$

, then it will be

$$\frac{\partial w_i}{\partial \mu_{ji}} = \frac{w_i}{\mu_{ji}} \tag{27}$$

The last partial derivative, Eq. 27 depends on the membership function we examine. The update equations for antecedent $c_{ij,}$ and σ_{ij} parameters of Gaussian function are:

$$c_{ij}(n+1) = c_{ij}(n) - \eta_c \cdot e \frac{(p_i x_1 + q_i x_2 + r_i) - y}{\sum\limits_{i=1}^{n} w_i} \cdot \left(\frac{(x_{ij} - c_{ij})}{\sigma^2_{ij}} \right) \mu_{ij}(x_j) \tag{28}$$

$$\sigma_{ij}(n+1) = \sigma_{ij}(n) - \eta_\sigma \cdot e \frac{(p_i x_1 + q_i x_2 + r_i) - y}{\sum\limits_{i=1}^{n} w_i} \cdot \left(\frac{(x_{ij} - c_{ij})^2}{\sigma^3_{ij}} \right) \mu_i(x_j) \tag{29}$$

The update equations for a_{ij} are, b_{ij} are respectively

$$\alpha_{ij}(n+1) = \alpha_{ij}(n) - \eta_\alpha \cdot e \frac{(p_i x + r_i) - y}{\sum\limits_{i=1}^{n} w_i} \cdot \frac{w_i}{\mu_{ij}(x_j)} \cdot \frac{2|x_j - a_{ij}|}{b_{ij}} \tag{30}$$

$$b_{ij}(n+1) = b_{ij}(n) - \eta_b \cdot e \frac{(p_i x + r_i) - y}{\sum\limits_{i=1}^{n} w_i} \cdot \frac{w_i}{\mu_{ij}(x_j)} \cdot \frac{1 - \mu_{ij}(x_j)}{b_{ij}} \tag{31}$$

In a similar fashion the update equations for sigmoidal shape fuzzy membership function can be derived. The next step is to define the initial values for antecedent parameters. In all cases we get as initial values for enter and bases parameters the mean and standard deviation. To be specific we get one sample where the returns on assets are negative and one sample where the returns are positive. The same procedure is followed for cash flow. So for center parameters a, c and c of triangle, Gaussian and sigmoid respectively we take the average for negative and positive samples. On the other hand for the base parameters, b, σ and a we take the standard deviations of the respective samples. For the center and consequent *RHS* parameters we set up the value 0.05 as the learning rate and for base parameters we set up the learning rates at 0.01.

4. Data

The sample period we examine in the current study is 2003-2009. We examine 15 Greek banks and the data are on weekly frequency. Additionally, the period 2003-2008 is used as the in-sample or training data period and the remaining period 2009 is used as the out-of-sample or testing data period. The notion of portfolio theory and

systematic risk was not developed at that time, and it was until later when Stone [1972] extended the market model by incorporating the effects of debt indices. To assess the effect of the market yield so we have constructed equally weighted stock portfolios for the following sectors the Greek

The General index of Athens stock market is used as proxy for the Greek banks, while the Libor of one and three months is used as the interest variable in equation (1). Additionally, we examine if the equally weighted portfolios returns, the General index of Athens stock exchange market returns and interest rate changes are stationary. To be specific we confirm this assumption by applying Augmented Dickey-Fuller-ADF [Dickey and Fuller, (1979)] unit root test and KPSS stationary test [Kwiatkowski *et al.*, (1992)]. The ADF test is defined from the following relation:

$$\Delta y_t = \mu + \gamma y_{t-1} + \phi_1 \Delta y_{t-1} + \dots + \phi_p \Delta y_{t-p} + \beta t + \varepsilon_t \tag{32}$$

, where y_t is the variable we examine each time. In the right hand of regression (32) the lags of the dependent variable are added with order of lags equal with p. Additionally, regression (32) includes the constant or drift μ and trend parameter β. The disturbance term is defined as ε_t. In the next step we test the hypotheses:

H_0: $\varphi=1$, $\beta=0$ against the alternative hypothesis H_1: $|\varphi|<1$

We accept that a variable is stationary if we reject the null hypothesis of unit root test. On the other hand in KPSS test series is assumed to be stationary under the null hypothesis. The series is detrended by regressing y on a random walk process x_t i.e., $x_t = x_{t-1} + u_t$ and a deterministic term βt

$$y_t = x_t + \beta t + \varepsilon_t \tag{33}$$

KPSS statistic is based on the residuals for the ordinary least squares regression (33). Let the partial sum series of ε_t be s_t. It is:

$$s_t = \sum_{j=1}^{t} e_j \tag{34}$$

The KPSS statistic is then defined as:

$$KPSS = T^{-2} \sum_{t=1}^{T} s^2_t / \hat{\sigma}^2 (p) \tag{35}$$

, where T is the number of sample and $\hat{\sigma}^2(p)$ is the long-run variance of ε_t and can be constructed from the residuals ε_t as:

$$\hat{\sigma}^2(p) = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_t^2 + \frac{2}{T} \sum_{t=1}^{p} w_j(p) + \sum_{t=j+1}^{T} \varepsilon_t \varepsilon_{t-j} \tag{36}$$

, where p is the truncation lag, $w_j(p)$ is an optional weighting function that corresponds to the choice of a special window. Under the null hypothesis of level stationary,

$$KPSS \rightarrow \int_0^1 V_1(r)^2 dx \tag{37}$$

, where $V_1(x)$ is a standard Brownian bridge: $V_1(r) = B(r) - rB(1)$ and $B(r)$ is a Brownian motion (Wiener process) on $r \in [0, 1]$. Because relation (37) is refereed in testing only on the intercept and not in the trend and as we are testing with both intercept and trend we have the second-level Brownian bridge $V_2(x)$ and it is:

$$KPSS \rightarrow \int_0^1 V_2(r)^2 dx \tag{38}$$

, where $V_2(x)$ is given by:

$$V_2(r) = W(r) + (2r - 3r^2)W_1 + (-6r + 6r^2)\int_0^1 W_s(s)ds \qquad (39)$$

In table 1 the results of unit root and stationary tests are reported. We conclude that all the variables are stationary, *I(0)*, based on ADF test, as we reject the null hypothesis in all levels of statistical significance. On the other hand we observe that the equally weighted stock portfolio returns and the General index returns are stationary in all levels of statistical significance, but the interest rate changes are stationary in α=0.05 and α=0.10.

Table 1.   ADF unit root and KPSS stationary tests

Variables	ADF t-stat.	KPSS LM-stat.	Critical values for ADF test[1]	Critical values for KPSS test[2]
3 month interest rate changes	-7.257	0.1970		
General index returns	-14.342	0.0699	α= 0.01, -3.983	α= 0.01, 0.216
Equally weighted portfolio returns of Greek Banks	-13.938	0.0552	α= 0.05, -3.422	α= 0.05, 0.146
			α= 0.10, -3.134	α= 0.10, 0.119

1. MacKinnon, (1996), 2. Kwiatkowski *et al.,* (1992)

4. Empirical Results

In table 2 we present the correlation coefficients and their associated *t-statistics* between interest rate changes and General Index returns of Athens stock market. We observe that the correlation coefficients are low except from some sub-periods, as in 2005 and 2008, and statistically significant, but still not even close to 1 or -1. Also the correlation in the overall period 2003-2009 we examine is very close to zero and in the case of 1 month interest rate changes the correlation coefficient is statistically significant.

Multicollinearity can still be a problem even when pair-wise correlations are small. Another way to detect multicollinearity in such situations is to calculate the *variance inflationary factors* (VIF's). There is a different *VIF* for each independent variable. Each independent variable's *VIF* measures how much the variance of its coefficient estimate has been inflated by multicollinearity. The ideal *VIF* for a variable is 1, and values higher than 10, or 4-5 proposed by other researchers, indicate the existence of multicollinearity. Another measure is the *tolerance* which is defined as *1/ VIF*, so the closer is the *tolerance* to zero the greater the degree of collinearity of that variable with the other regressors and the closer *tolerance* is to 1, the greater the evidence that the variable is not collinear with the other regressors. The *VIF* is simply computed by finding the inverse of the correlation matrix and taking the diagonal elements. It becomes clear that from the results of tables 2 and 3 the *VIF* values are almost 1 or very close to 1, indicating the rejection of multicollinearity. Furthermore, *tolerance* is very close to 1 so there is evidence that the variables are not correlated. So there is no reason to take any additional procedure to solve for multicollinearity.

In table 3 the estimation results with GARCH (1,1) and three month interest rates are reported. We do not present the results with other interest rates as one, six or twelve months as the results are similar and the conclusions are exactly the same. From the results of table 3 we observe that only coefficient β_1 is positive and statistically significant. So if the General markets returns are increased then the common bank stock returns are increased too. Based on the diagnostic tests we reject the autocorrelation and ARCH effects.

Our results are consistent with those of Chance and Lane [1980] who found that fewer than 2 per cent of the banks exhibited significant interest rate sensitivity to a short-, medium- or long-term treasury index and with those of Lloyd and Shick [1977] who support that stock returns only marginally explained by the interest rate factor and they find no incremental explanatory power for interest rate changes. Additionally our findings confirm the arguments of other authors [Choi and Elyasiani, (1996); Allen and Jagtiani, (1997); Benink and Wolff, (2000)], who conclude that interest rate sensitivity has decreased in the late 1980's and early 1990's due to the availability of interest rate derivatives contracts that can be used for hedging purposes. Also our empirical findings are consistent with the results of Beirne *et al*. [2009] who examine 13 European countries, including Greece and Germany, as also examine USA and Japan and find that interest rate changes have insignificant effects on stock returns, while find significant effects, only Sweden with both short-term and long-term interest

rates, in Ireland and Netherlands, only with long-term interest rates and finally in Italy only with short-term interest rates.

In table 4 the estimated fuzzy antecedent and consequent parameters for ANFIS with triangle and Gaussian membership functions are reported, while the estimated coefficients for ANFIS with sigmoidal shaped function are provided in table 5.

Table 2. Correlation and VIF between interest rates changes and General index

Period	Correlation coefficients 3-month interest rate change	VIF 3-month interest rate change
2003	-0.071 (-3.584)	10.041
2004	-0.085 (-4.277)	10.063
2005	0.137 -6.949	10.173
2006	0.251 -12.971	10.672
2007	0.146 -7.396	10.218
2008	-0.240 (-12.364)	10.611
2003-2008	0.0189 -7.322	10.005

* t-statistics in parentheses

Table 3. GARCH modeling for the two-factor index model and three months interest rates

	β_0	β_1	β_2
Mean equation	-0.00135 [-0.784]	0.76046 [18.943]*	0.01230 [1.194]*
	γ_0	γ_1	γ_2
Variance equation	0.00030 [3.799]*	0.00030 [3.726]*	1.35e-05 [3.829]*
Diagnostic tests	Log-Likelihood	$LBQ^2 (8)^1$	ARCH-LM $(5)^2$
	659.475	0.8973 (0.999)	0.1215 (0.9875)

* denotes statistical significant in α=0.01, t-statistics in brackets, p-values in parentheses,
1. ARCH-LM is for Autoregressive conditional heteroskedasticity test of residuals with 5 lags,
2. LBQ^2 is the Ljung-Box test on squared standardized residuals with 8 lags.

Table 4. Final fuzzy antecedent and consequent parameters after the training process for ANFIS with triangle and Gaussian membership functions

ANFIS with triangle membership function				ANFIS with Gaussian membership function			
Antecedent parameters for General index returns		Antecedent parameters for interest rate changes		Antecedent parameters for General index returns		Antecedent parameters for interest rate changes	
α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
-0.0197	-0.0554	-0.0732	0.0412	-0.0753	0.0493	-0.0087	-0.0044
b_1	b_2	b_1	b_2	b_1	b_2	b_1	b_2
-0.0238	0.1086	0.1861	0.0708	0.1187	0.0889	0.0502	-0.0073
Consequent parameters				Consequent parameters			
p_1	p_2	p_3	p_4	p_1	p_2	p_3	p_4
0.1592	-0.0116	-3.467	-0.2206	-0.3438	0.3683	0.7805	-0.8949
q_1	q_2	q_3	q_4	q_1	q_2	q_3	q_4
-0.6032	0.6208	-1.355	0.3406	-0.0378	1.7632	1.9005	-0.0854
r_1	r_2	r_3	r_4	r_1	r_2	r_3	r_4
-0.0347	0.0014	0.0508	0.0021	-0.0025	-0.0085	0.1603	-0.1596

Table 5. Final fuzzy antecedent and consequent parameters after the training process for ANFIS with sigmoidally shaped membership function

ANFIS with sigmoidally shaped membership function

Antecedent parameters for General index returns		Antecedent parameters for interest rate changes	
α_1	α_2	α_1	α_2
-0.0197	-0.0554	-0.0732	0.0412
b_1	b_2	b_1	b_2
-0.0238	0.1086	0.1861	0.0708
Consequent parameters			
p_1	p_2	p_3	p_4
-12.448	14.322	10.925	-12.756
q_1	q_2	q_3	q_4
21.433	-11.896	-35.813	40.972
r_1	r_2	r_3	r_4
0.3264	-0.3513	-0.0453	0.0244

From tables 4 and 5 we can derive various rules, which can help us to draw the effects of interest rate changes and General Index returns on Greek bank stock returns and therefore to investigate the behavior of stock returns. For example with ANFIS and triangle function we have the following:

If the General index returns are negative and interest rate changes are negative then we have

$f_1 = 0.1592x_1 - 0.6032 x_2 - 0.0347$

If the General index returns are negative and interest rate changes are positive then

$f_2 = -0.0116x_1 + 0.6208 x_2 + 0.0014$

If the General index returns are positive and interest rate changes are negative then

$f_3 = -3.467x_1 - 1.355x_2 + 0.0508$

If the General index returns are positive and interest rate changes are positive then

$f_4 = -0.2206x_1 + 0.3406x_2 + 0.0021$

Let suppose for example that both General index returns and interest rate changes are positive with values 0.0024 and 0.0410 respectively, and then we will have:

$f_4 = -0.2206x_1 + 0.3406x_2 + 0.0021 = -0.000529 + 0.0139 + 0.0021 = 0.0155$

So, when both inputs are positive and with the specific values we can have positive stock returns. Because there are different values then the positive returns can be made negative. For example we consider General index returns and interest rate changes are positive with values 0.0240 and 0.0010 respectively then it will be:

$f_4 = -0.2206x_1 + 0.3406x_2 + 0.0021 = -0.00529 + 0.00034 + 0.0021 = -0.00285$

So based on the new values the positive interest rate changes and stock index returns have a negative impact on common bank stock returns. Let us take another example, where we consider positive General index returns negative interest rate changes, with values 0.0024 and -0.0078 respectively.

$f_3 = -3.467x_1 - 1.355x_2 + 0.0508 = -0.00832 + 0.0105 + 0.0508 = 0.053$

Now let's take new values where General index returns are positive, but interest rate changes are negative, with values 0.024 and -0.0158

$f_3 = -3.467x_1 - 1.355x_2 + 0.0508 = -0.0832 + 0.0214 + 0.0508 = -0.011$

Hence, in this case we get negative stock returns instead of positive we found previously. The ANFIS technology is much more useful for the practitioners because they are able to determine more efficiently their portfolio as also they can be more flexible. For example based on the regression we estimated we find that there are not significant effects. Furthermore, if for example we had found significant and negative effects, this is not useful for the financial managers and traders, because the sign is changed in each period, at least on high frequency, as daily or weekly, based on the behavior and rules we have defined for the inputs. Additionally, if the sign remains constant for the long term as yearly, this is not again useful or practitioners and traders in financial industry, because they work and trade in daily frequency and short term periods. So in this case the conventional econometric modeling is not very helpful for practicing purposes. In tables 6 and 7 the Root Means Squared Error (RMSE), Mean Absolute Error (MAE) and the correct percentage sign of stock returns are reported. We observe that in ANFIS RMSE and MAE are lower to the respective values of GARCH process in both in-sample and out-of-sample periods. Furthermore, in tables 6 and 7 we present the percentage of the correct sign of stock returns. The last one is preferred because researchers have argued that the sole use of mean squared error and mean absolute error may be inappropriate for financial data and particularly for market practitioners and financial traders who may be more interest in the sign of forecasts rather than the magnitude of forecast errors, as the former provides information with respect to buy and sell signals. Besides the fact that if it is not impossible, it is very difficult to predict the actual value, in practice the agents and traders in financial markets are interesting more in the ability of models to give the correct signaling.

More specifically, based on the prediction of the correct sign on stock returns ANFIS outperforms significant GARCH modeling, as for in –sample period we predict correctly the sign at 93.33, 90.00 and 86.67 per cent with sigmoidal shape, Gaussian and triangle membership functions respectively, while the respective percentage is 76.67 with GARCH process. Additionally, in the out-of-sample period, which is of greatest interest and importance for the financial risk managers and traders, we predict in the best and worst cases 82.69 and 80.76 per cent respectively with ANFIS, while with GARCH model we predict the correct stock returns sign at 71.15 per cent.

Table 6. Forecasting performance for GARCH and ANFIS with triangle function

	GARCH		ANFIS with triangle function	
	In-sample	Out-of-sample	In-sample	Out-of-sample
RMSE	0.03179	0.03971	0.02940	0.03853
MAE	0.02044	0.03261	0.01886	0.03038
Correct Percentage Sign	76.67	71.15	90.00	80.76

Table 7. Forecasting performance for ANFIS with Gaussian and Sigmoidal function

	ANFIS with Gaussian function		ANFIS with Sigmoidal function	
	In-sample	Out-of-sample	In-sample	Out-of-sample
RMSE	0.02968	0.03743	0.02871	0.03841
MAE	0.01895	0.02925	0.01810	0.03032
Correct Percentage Sign	86.67	82.69	93.33	82.69

Conclusions

We examined the current effects of interest rate changes in stock returns of the banking sector in Athens stock exchange market. We concluded that we reject the effects of interest rate changes based on GARCH model as we found them to be statistically insignificant. Additionally, we proposed ANFIS technology with three membership functions, the triangle, the Gaussian and the sigmoidal shaped function. We propose ANFIS in order to overcome the problems and the restrictions of econometric approaches. This is because there is not always a unique sign or effects of independent variables on the dependent because there is not a straight forward way to identify the effects of inputs to outputs. To be specific it is not necessary that there will be constant signs or effects during a specific period we examine but these are changed in each observation and in each period. So in the case we examine, where we have weekly data, in each week, different effects will be reported based on the values and the rules of the system

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