The Prediction of Interest Rate Using Artificial Neural Network Models

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Abstract

Artificial Neural Network(ANN) models were used for forecasting interest rate as a new methodology, which has proven itself successful in financial domain. This research intended to construct ANN models which can maximize the performance of prediction, regarding Corporate Bond Yield(CBY) as interest rate.

Synergistic Market Analysis(SMA) was applied to the construction of models [Freedman et at.]. In this aspect, while the models which consist of only time series data for corporate bond yield were developed, the other models generated through conjunction and reorganization of fundamental variables and market variables were developed.

Every model was constructed to predict 1, 6, and 12 months after and we obtained 9 ANN models for interest rate forecasting. Multi-layer perceptron networks using backpropagation algorithm showed good performance in the prediction for 1 and 6 months after.

Introduction

Perhaps more efforts and time have been spent on forecasting stock prices than on any other financial subject, but more people are affected by the change in the level of interest rate than the movements of stock prices [Martin J. Pring, 1981]. In addition, the increase of the financial risk due to the liberalization of interest rate enhances the importance of the level of interest rate. The earning and loss may be determined by the level of interest rate.

Most previous researches on interest rate focused only on applying the traditional theory of interest rate determination to Korean situation and testing it empirically. Therefore, the construction of model for interest rate forecasting comes to be needed because the interest rate determination model is insufficient to be applied to interest rate forecasting.

Interest rate shows the strong characteristic of random walk and high volatility so that they aren't easy to predict with time series models [Murphy, 1990]. Park(1993) also found that Korean interest rate shows the same results. In recent researches, it was proved that ANN was very useful and had high forecast efficiency in stock market and credit rating etc. ANN is insensitive to such problems as cointegration relations or unstationarity among variables which should be solved to apply time series models.

ANN model for forecasting interest rate will be constructed for various prediction periods and we will test how long period ANN models are capable to forecast.

Case Selection

Corporate Bond Yield(CBY) is mainly regarded as a representative nominal interest rate and bank-guaranteed corporate bonds with three year maturity constitute the majority of corporate bonds. Therefore the bank-guaranteed corporate bond yield with three year maturity should be target for interest rate forecast.

Variable Selection

Mendelsohn L. B.(1989) said that historically, two distinct schools of analysis, fundamental and technical, have been pursued [recited by Freedman et al., 1995]. Fundamental analysis paid great attention to basic economic supply and demand factors underlying the markets, whereas technical analysis concentrated internally on a single market to interpret the movement and behavior of prices as a guide to decision making. More recently, intermarket analysis, which looks intuitively at relationships between markets, - usually through the subjective examination of price charts - has become fashionable. Yet, none of these approaches by itself is sufficient in today's market.

Therefore Freedman et al.(1995) proposed the new method of analysis, referred to as Synergistic Market Analysis(SMA), which encompasses the more narrowly defined extent schools of technical, fundamental, and intermarket analysis. They insisted that the synergistic approach benefits from the use of artificial intelligence technologies, and other appropriate mathematical tools.

However, some inputs, composed by more than one variables, may be used for neural network. Also in some cases, there may not be clear cuts among technical, fundamental, and intermarket variables. Although these problems may happen, input variables can be grouped for the model construction, especially for neural network.

First, CBY was considered in respect of autoregression. Many time series models such as ARIMA and VAR(Vector Autoregressive) model presented CBY as an important input variable for CBY forecast model. 3 month time lag was accepted becasue it was learned well in various cases. So CBYt, CBYt-1, and CBYt-2 are used as input variables. (see Table 1)

Second, fundamental economic variables are considered. Price increase rate is generally related to nominal interest rate by Fisher Effect [Fama, 1975]. CPI(Consumer Price Index) was used for price increase rate. Also HPI (house price index) are used for reflecting Fisher effect. GNP is generally used as an index showing the level of economic activity, but it is available only quarterly. So IP(Index of Industrial Production) was used for the level of economic activity. Currency index was included for the purpose of reflecting liquidity effect. M2 was used for total currency.

In open economy, domestic interest rate might be affected by foreign interest rate and foreign exchange rates because arbitrage transactions occur when domestic and foreign interest rate are different. Edwards and Khan(1985) explained that domestic interest rate reacts slowly to foreign effect. Singapore and Colombia were analyzed empirically by them. Singapore has completely open economy and Colombia lies between open and closed economy. The result was that foreign factors mainly explained Singapore's interest rate, but Colombia reacted sensitively on both domestic and foreign factors. Therefore foreign exchange rate for US $ was selected here since Korean economy lies nearby open economy in some degree.

Third, the market variables were included, which affect the relation between supply and demand of corporate bond market. One is the total value of note exchange and the other is the net increasing amount of corporate bond issued subtracting the previous month from current month. In the view of corporate bond as a kind of commodity, these variables were selected.

Structure of Model

ANN models were constructed for interest rate forecast as follows. Each model was divided into three types accordance with prediction for 1, 6, and 12 months after.

[1] Model 1

Model 1 is constructed only with CBY variables. Time lag is 3-month and 1, 6, and 12 months after CBY is predicted. CBY are averaged monthly.

$$CBY_{t+k} = f(CBY_t, CBY_{t-1}, CBY_{t-2}) \quad k = 1, 6, 12$$

[2] Model 2

Model 2 is constructed with CBY and fundamental variables such as IP, CPI, M2 and FX. Every input variable is based monthly pattern. IP, CPI, M2, FX are the increasing amount over the same periods in the previous year. That is, $X'_t = X_t - X_{t-12}$.

$$CBY_{t+k} = f(IP_t, CPI_t, M_{2t}, FX_t, CBY_t, CBY_{t-1}, CBY_{t-2}) \quad k = 1, 6, 12$$

[3] Model 3

Model 3 was constructed by three fundamental variables and by two market variables in the aspect of supply and demand of CBY. And CBY was added to this model. Real currency amount was obtained from the total currency M2 divided by CPI. Expected inflation was also obtained from CPI divided by HPI due to increasing rate of real property affected by expected psychology. Index for economic activity level was substituted by IP(Index of Industrial Production).

RC, EI, IP, BILL and NETCB, here, are increasing amount over the previous month and they were all converted into annual rate through continuous compounding equation which was used by Kim, Y. J. (1993). That is to say, X's annual rate by continuous compounding equation is $100 \times \{(\frac{X_t}{X_{t-1}})^{12} - 1\}$.

$$CBY_{t+k} = f(RC_t, EI_t, IP_t, BILL_t, NETCB_t, CBY_t, CBY_{t-1}, CBY_{t-2}) \quad k = 1, 6, 12$$

RCt : real currency amount in t month, M_2 / CPI_t

EIt : expected inflation in t month, CPI_t / HPI_t

Artificial Neural Network

Kolmogrov's theorem [Hecht and Nielsen, 1990] states that for a three layered neural network with n inputs, 2n+1 nodes in hidden layer, and m outputs, there exists a continuous mapping function f. Because this theorem is an existence theorem only, it does not tell us how to find the mapping function. Hecht and Nielsen(1990) shows that a three-layered backpropagation neural network can approximate a function f that maps the inputs to the outputs. This research indicates that, at most, one hidden layers are needed with maximum 2n+1 hidden nodes. Therefore the number of hidden node was searched by all odd numbers 1 to 2n+1.

Backpropagation neural networks, if trained infinitely, suffers from overfitting [Hecht and Nielsen, 1990]. Hecht and Nielsen(1990) suggests that there should be two samples that should be used for training. A samples that is used for training the network and the other used to validate the network. This second sample is different from a holdout sample, since it is used during training to identify the point at which overtraining starts to occur.

The performance of the network using the training data improves asymptotically and a point is reached where further training does not decrease error. Performance using the test data improves until it reaches a point where further training should be stopped at this point. In this study we used the above methodology to overcome the problem of overtraining.

Result of Neural Network Experiment

The neural network were built using a commercially available software package NeuroShell II developed by Ward System Group Inc. In building neural network models for forecasting corporate bond yield as nominal interest rate, data samples include 3 types of data set. Two sets of data were used to train the networks. The training data start January 1987 through data preprocessing and exclude test data set. The training data consist of 69 patterns and 12 patterns were randomly picked for testing from the January 1987 through September 1993. To measure neural network performance, holdout sample data which contains 12 patterns were used. Each model consists of 3 types of neural network to predict 1, 6, and 12 month later.

All of the best neural network models were selected in two aspects. One is for hidden node. The number of hidden nodes was selected among searching 1 to 2n+1(n = number of input variables). The other was for RMSE (Root Mean Square Error). The learning was controlled by the epochs at which RMSE reached minimum in test data. Table 1, 2, and 3 show the result of model 1, 2, and 3 respectively.

To compare neural network models to MLR(Multiple Linear Regression) and ARIMA, first, we used MLR to compare the performances.

Model 1	Training sample	Test sample	Holdout sample
1 month	0.537	0.658	0.302
6 month	2.139	1.553	1.415
12 month	1.715	1.834	1.637

Table 1. The RMSE for Neural network *model 1*

Model 2	Training sample	Test sample	Holdout sample
1 Month	0.494	0.562	0.238
6 Month	0.352	0.787	0.853
12 Month	0.159	0.754	1.407

Table 2. The RMSE for Neural network *model 2*

Model 3	Training sample	Test sample	Holdout sample
1 Month	0.393	0.716	0.343
6 Month	1.333	1.450	1.057
12 Month	0.396	1.475	2.456

Table 3. The RMSE for Neural network *mode 3*

The prediction result of ANN, MLR, and ARIMA are summarized in Table 4.

	NN 1	NN 2	NN 3	MLR 1	MLR 2	ARIMA
1 month	0.302	0.238	0.343	1.649	4.627	1.015
6 month	1.415	0.853	1.057	5.527	1.902	1.004
12 month	1.637	1.407	2.456	1.290	1.902	1.009

Table4. RMSE for Neural network, MLR, and ARIMA

Statistical Test for Models

To see that there are differences among the errors of models, we performed the paired t-test between each model. The error was calculated by the following method.

$E_i = | R_i - P_i |$ $\quad i = 1,2, ...,12$

where E is error of model, R is real value, P is predicted value, and i means number in holdout sample data.

The results of the paired t-test are shown in Table 5, 6, and 7. Each paired t-test was performed with null hypothesis as follows:

Ho : $E_c = E_r$

where E_c is error of column side model and E_r is error of row side model

In summary, in prediction for 1 months after, model 1,model 2, and model 3 are not identical in 5% significance level (see Table 5). Model 2 is superior only to MLR 1 and MLR 2 in prediction for 6 months after. It is not significant statistically in 5% significant level among other neural network models (see Table 6). Although ARIMA showed the best performance in prediction for 12 months after, but was not statistically significant in 5% significant level (see Table7).

	MLR1	MLR2	NN1	NN2	NN3
ARIMA	-3.32*	-7.27*	3.96*	4.96*	3.76*
MLR1		-6.32*	5.41*	6.19*	5.17*
MLR2			7.59*	7.78*	7.08*
NN1				0.74	-0.96
NN2					-1.70

Table 5. Paired t-test of 1 month period.
($| t | = 1.80$, $\alpha = 0.05$, * : significant)

	MLR1	MLR2	NN1	NN2	NN3
ARIMA	-7.01*	-0.10	-1.42	0.32	-0.03
MLR1		0.540	4.64*	6.83*	7.84*
MLR2			-1.05	0.38	0.07
NN1				1.65	0.99
NN2					-0.32

Table 6. Paired t-test of 6 month period.
($| t | = 1.80$, $\alpha = 0.05$, * : significant)

	MLR1	MLR2	NN1	NN2	NN3
ARIMA	-0.60	-4.62*	-4.37*	-0.87	-4.75*
MLR1		-2.71*	-1.12	-0.40	-2.63*
MLR2			2.55*	2.11*	1.13
NN1				0.54	-2.78*
NN2					-1.44

Table 7. Paired t-test of 12 month period.
($| t | = 1.80$, $\alpha = 0.05$, * : significant)

Conclusion and Further Research

We constructed various neural network models to find an appropriate model according to term period for prediction. The experimental result showed that the ability of prediction for CBY is significant statistically by paired t-test. We focused on construction of neural network model from the view of how many period ahead predicting CBY.

We tried to combining market variables and fundamental economic variables in the neural network models..

To forecast long period, the variables should be considered, which have characteristic for long period. Also, the variables which are announced by authorized institute such as KDI(Korea Development Institute) and the Bank of Korea, can be used as input variables for long period prediction.

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