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# Using change-point detection to support artificial neural networks for interest rates forecasting

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**Abstract**

Interest rates are one of the most closely watched variables in the economy. They have been studied by a number of researchers as they strongly affect other economic and financial parameters. Contrary to other chaotic financial data, the movement of interest rates has a series of change points owing to the monetary policy of the US government. The basic concept of this proposed model is to obtain intervals divided by change points, to identify them as change-point groups, and to use them in interest rates forecasting. The proposed model consists of three stages. The first stage is to detect successive change points in the interest rates dataset. The second stage is to forecast the change-point group with the backpropagation neural network (BPN). The final stage is to forecast the output with BPN. This study then examines the predictability of the integrated neural network model for interest rates forecasting using change-point detection. 

*Keywords*: Change point; Artificial neural networks; Interest rates; Pettitt test; Integrated model

## 1. Introduction

Interest rates are one of the most closely watched variables in the economy. Their movements are reported almost daily by the news media as they directly affect our everyday lives and have important consequences for the economy. There exist extensive studies in this area using statistical approaches, such as term structure models, vector autoregressive (VAR) models, autoregressive conditionally heteroskedastic (ARCH)—generalized autoregressive conditionally heteroskedastic (GARCH) models and other time series analysis approaches.

Currently, several studies have demonstrated that artificial intelligence (AI) approaches, such as fuzzy theory (Ju, Kim & Shim, 1997) and neural networks (Deboeck & Cader, 1994), can be alternative methodologies for the chaotic interest rates data (Jaditz & Sayers, 1995; Larrain, 1991; Peters, 1991). Previous work in interest rates forecasting tend to use statistical techniques and AI techniques in isolation. However, an integrated approach, which makes full use of statistical approaches and AI techniques, offers the promise of increasing performance over each method alone (Chatfield, 1993). It has been proposed that the integrated neural network models combining two or more models have the potential to achieve a high predictive performance in interest rates forecasting (Kim & Noh, 1997).

In general, interest rates data is controlled by government's monetary policy more than other financial data (Bagliano & Favero, 1999; Christiano, Eichenbaum & Evans, 1996; Gordon & Leeper, 1994; Leeper, 1997; Strongin, 1995). Especially, banks play a very important role in determining the supply of money. Much regulation of these financial intermediaries is intended to improve their control. One crucial regulation is reserve requirements, which make it obligatory for all depository institutions to keep a certain fraction of their deposits in accounts with the Federal Reserve System, the central bank in US (Mishkin, 1995). The government takes intentional action to control the currency flow that has direct influence upon interest rates. Therefore, we can conjecture that the movement of interest rates has a series of change points, which occur because of the monetary policy of the government.

Based on these inherent characteristics in interest rates, this study suggests the change-point detection for interest rates forecasting. The proposed model consists of three stages. The first stage is to detect successive change points in the interest rates dataset. The second stage is to forecast the change-point group with BPN. The final stage is to forecast the output with BPN. This study then examines the predictability of the integrated neural network models for interest rates forecasting using change-point detection.

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Through the discovery of different patterns in the US Treasury securities, the focus then shifts to the change-point detection-assisted modeling of Treasury bill rates with 1 years' maturity and Treasury bond rates with 30 years' maturity. Input variable selection is based on the causal model of interest rates presented by the econometricians. To explore the predictability, we divided the interest data into the training data over one period and the testing data over the next period. The predictability of interest rates is examined using the metrics of the root mean squared error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE).

In Section 2, we outline the development of change-point detection and its application to the financial economics. Section 3 describes the proposed integrated neural network model details. Sections 4 and 5 report the processes and the results of the case study. Finally, the concluding remarks are presented in Section 6.

## 2. Change-point detection

### 2.1. Application of change-point detection in the financial economics

Financial analysts and econometricians have frequently used piecewise-linear models that also include change-point models. They are known as models with structural break in the economic literature. In these models, the parameters are assumed to shift—typically once—during a given sample period and the goal is to estimate the two sets of parameters as well as the change point or structural break.

This technique has been applied to macroeconomic time series. The first study in this field is conducted by Perron (1989, 1990) and Rapport and Reichlin (1989). From then on, several statistics have been developed that work well in a change-point framework, all of which are considered in the context of breaking the trend variables (Banerjee, Lumsdaine & Stock, 1992; Christiano, 1992; Perron, 1995; Vogelsang & Perron, 1995; Zivot & Andrews, 1992). In those cases where only a shift in the mean is present, the statistics proposed in the papers by Perron (1990) or Perron and Vogelsang (1992) stand out. However, some variables do not show just one change point. Rather, it is common for them to exhibit the presence of multiple change points. Thus, it may be necessary to introduce multiple change points in the specifications of the models. For example, Lumsdaine and Papell (1997) considered the presence of two or more change points in the trend variables. In this study, it is assumed that the Treasury security rates can have two or more change points as well as just one change point.

There are a few artificial intelligence models to consider the change-point detection problems. Most of the previous research has a focus on the finding of unknown change points for the past, not the forecast for the future (Li & Yu, 1999; Wolkenhauer & Edmunds, 1997). Our model obtains intervals divided by change points in the training phase, identifies them as change-point groups in the training phase, and forecasts to which group each sample is assigned in the testing phase. It will be tested whether the introduction of change points to our model may improve the predictability of interest rates.

In this study, a series of change points will be detected by the Pettitt test, a nonparametric change-point detection method, as nonparametric statistical property is a suitable match for a neural network model that is a kind of nonparametric method (White, 1992). In addition, the Pettitt test is a kind of Mann–Whitney type statistic, which has a remarkably stable distribution and provides a robust test of the change point resistant to outliers (Pettitt, 1980b). In this point, the introduction of the Pettitt test is fairly appropriate to the analysis of chaotic interest rates data.

### 2.2. The Pettitt tests

The Pettitt tests assume that the observations form an ordered sequence and that initially the distribution of responses has one median and at some point there is a shift in the median of the distribution. $H_0$ is the null hypothesis that there is no change in the location parameter (i.e. the median) of the sequence of observations, and $H_1$ is the alternative hypothesis that there is a change in the location parameter of the sequence.

There are two kinds of change-point detection tests. One is appropriate when the data is binary and consists of observations with some binomial process (Pettitt, 1980a). Another test assumes that the data are continuous (Pettitt, 1979). The logic of the tests is similar although the computational formulas are different. We use the continuous type as we forecast the real value of interest rates. The Pettitt test is explained as follows.

First, each of the observations $X_1, X_2, \ldots, X_N$ must be ranked from 1 to $N$. Let $r_i$ be the rank associated with the observation $X_i$. Then at each place $j$ in the series, we calculate

$$W_j = \sum_{i=1}^{j} r_i, \quad j = 1, 2, \ldots, N-1 \tag{1}$$

which is the sum of the ranks of the variables at or before the point $j$. Next for each point in the sequence, calculate $2W_j - j(N+1)$. Then set

$$K_{m,n} = \max\left|2W_j - j(N+1)\right| \quad j = 1, 2, \ldots, N-1 \tag{2}$$

The value of $j$ where the maximum in Eq. (2) occurs is the estimated change point in the sequence and is denoted $m$. $N - m = n$ is the number of observations after the change point. Thus, $K_{m,n}$ is the statistic which divides the sequence into $m$ and $n$ observations occurring before and after the change, respectively.

Whether this value of $K_{m,n}$ is larger than we would expect under $H_0$ can be tested by referring to a table of the sampling

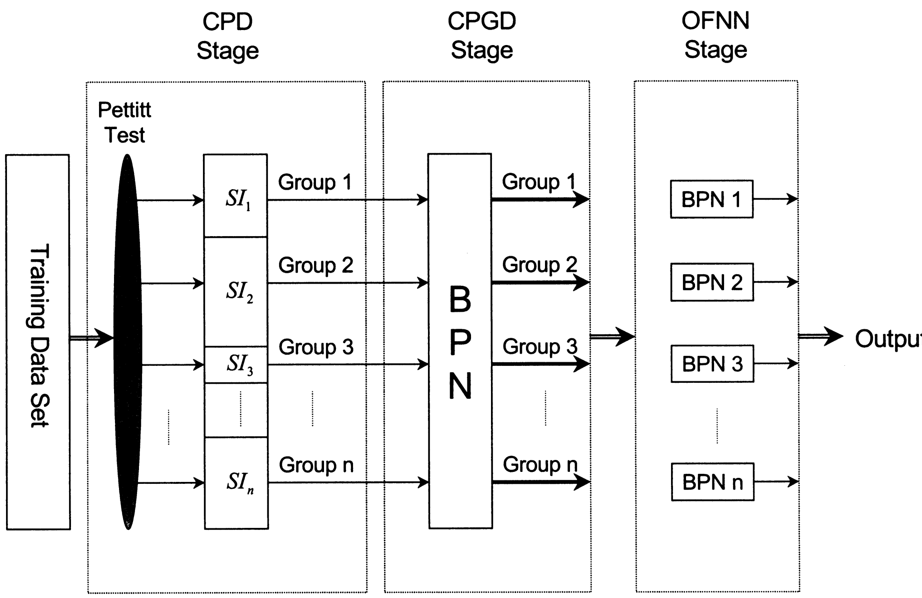



Fig. 1. Architecture of the proposed model using change-point detection.

distribution of $W_j$, the sum of ranks. If $W$ exceeds the tabled value of $W$ at the appropriate significance level, we may reject $H_0$ that there is no change in distribution.

If $N$ becomes large, $W$ is approximately normally distributed with mean $m(N+1)/2$ and variance $mn(N+1)/12$ under $H_0$. Thus, when the series is long, the test for change may be carried out and tested using the standard normal distribution table by transforming $W$ into $Z$:

$$Z = \frac{W + h - m(N+1)/2}{\sqrt{mn(N+1)/12}} \tag{3}$$

where $h = -0.5$ if $W > m(N+1)/2$ and $h = +0.5$ if $W < m(N+1)/2$.

The Pettitt test detects a possible change point in the time sequence dataset. Once the change point is detected through the test, then the dataset is divided into two intervals. The intervals before and after the change point form homogeneous groups that take heterogeneous characteristics from each other. This process becomes a fundamental part of the binary segmentation method explained in Section 3.

## 3. Model specification

Statistical techniques and neural network learning methods have been integrated to forecast the treasury security rates. The advantages of combining multiple techniques to yield synergism for discovery and prediction have been widely recognized (Gottman, 1981; Kaufman, Michalski & Kerschberg, 1991). BPN is applied to our model as BPN has been used successfully in many applications such as classification, forecasting and pattern recognition (Patterson, 1996).

In this section, we discuss the architecture and the characteristics of our model to integrate the change-point detection and the BPN. Fig. 1 shows the architecture of our model. Based on the Pettitt test, the proposed model consists of three stages: (1) the change-point detection (CPD) stage; (2) the change-point-assisted group detection (CPGD) stage; and (3) the output forecasting neural network (OFNN) stage. The BPN is used as a classification tool in CPGD and as a forecasting tool in OFNN.

### *3.1. The CPD stage: construction and analysis on homogeneous groups*

The Pettitt test is a method to find a change-point in the time series data (Pettitt, 1979). It is known that interest rates at time $t$ are more important than the fundamental economic variables in determining interest rates at time $t+1$ (Larrain, 1991). Thus, we apply the Pettitt test to interest rates at time $t$ in the training phase. The interval made by the test is defined as the significant interval, labeled SI, which is identified with a homogeneous group. Multiple change points are obtained under the binary segmentation method (Vostrikova, 1981) which is explained as follows:

Step 1. Find a change point in $1 \sim N$ intervals by the Pettitt test. If $r_1$ is a change point, $1 \sim r_1$ intervals are regarded as $SI_1$ and $(r_1+1) \sim N$ intervals are regarded as $SI_2$. Otherwise, it is concluded that there does not exist a change point for $1 \sim N$ intervals ($1 \le r_1 \le N$).

Step 2. Find a change point in $1 \sim r_1$ intervals by the Pettitt test. If $r_2$ is a change point, $1 \sim r_2$ intervals are regarded as $SI_{11}$ and $(r_2+1) \sim r_1$ intervals are regarded as $SI_{12}$. Otherwise, $1 \sim r_1$ intervals are regarded as $SI_1$ like Step 1 ($1 \le r_2 \le r_1$).Find a change point in $(r_1+1) \sim N$ intervals by the Pettitt test. If $r_3$ is a change point,

Table 1
Description of input variables

| Variable name | Description |
|---|---|
| M2 | Money stock |
| CPI | Consumer price index |
| ERIR | Expected real interest rates |
| IPI | Industrial production index |

$(r_1 + 1) \sim r_3$ intervals are regarded as $SI_{21}$ and $(r_3 + 1) \sim N$ intervals are regarded as $SI_{22}$. Otherwise, $(r_1 + 1) \sim N$ intervals are regarded as $SI_2$ like Step 1 ($r_1 \leq r_3 \leq N$).

Step 3. By applying the same procedure of Steps 1 and 2 to subsamples, we can obtain several significant intervals under the dichotomy.

We, first of all, have to decide the number of change points. If just one change point is assumed to occur in a given dataset, only the first step will be performed. Otherwise, all of the three steps will be performed successively. This process plays a role of clustering that constructs groups as well as maintains the time sequence. In this point, the CPD stage is distinguished from other clustering methods such as the *k*-means nearest neighbor method and the hierarchical clustering method which classify data samples by the Euclidean distance between cases without considering the time sequence. In addition, we analyze the characteristics of groups according to descriptive statistics including the mean and the variance, and also observe the density plot of groups as the classification accuracy is highly sensitive to the density of the samples (Wang, 1995).

### *3.2. The CPGD stage: forecast the group with BPN*

The significant intervals in the CPD stage are grouped to detect the regularities hidden in interest rates. Such groups represent a set of meaningful trends encompassing interest rates. As those trends help to find regularity among the related output values more clearly, the neural network model can have a better ability of generalization for the unknown data. This is indeed a very useful point for sample design. In general, the error for forecasting may be reduced by making the subsampling units within groups homogeneous and the variation between groups heterogeneous (Cochran, 1977). After the appropriate groups hidden in interest rates are detected by the CPD stage, BPN is applied to the input data samples at time *t* with group outputs for $t + 1$ given by CPD. In this sense, CPGD is a model that is trained to find an appropriate group for each given sample.

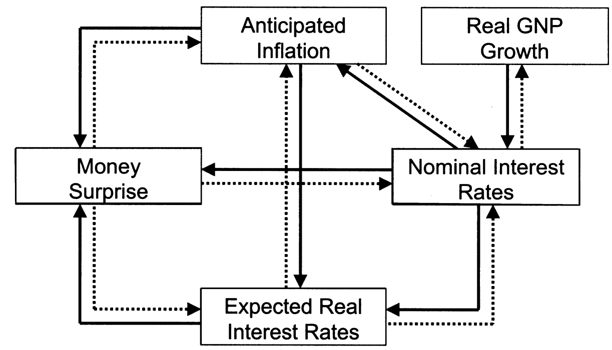



Fig. 2. The economic model under the Fisher-type interest rate equation.

### *3.3. The OFNN stage: forecast the output with BPN*

OFNN is built by applying the BPN model to each group. OFNN is a mapping function between the input sample and the corresponding desired output (i.e. Treasury security rates). Once OFNN is built, then the sample can be used to forecast the Treasury security rates.

## 4. Data and variables

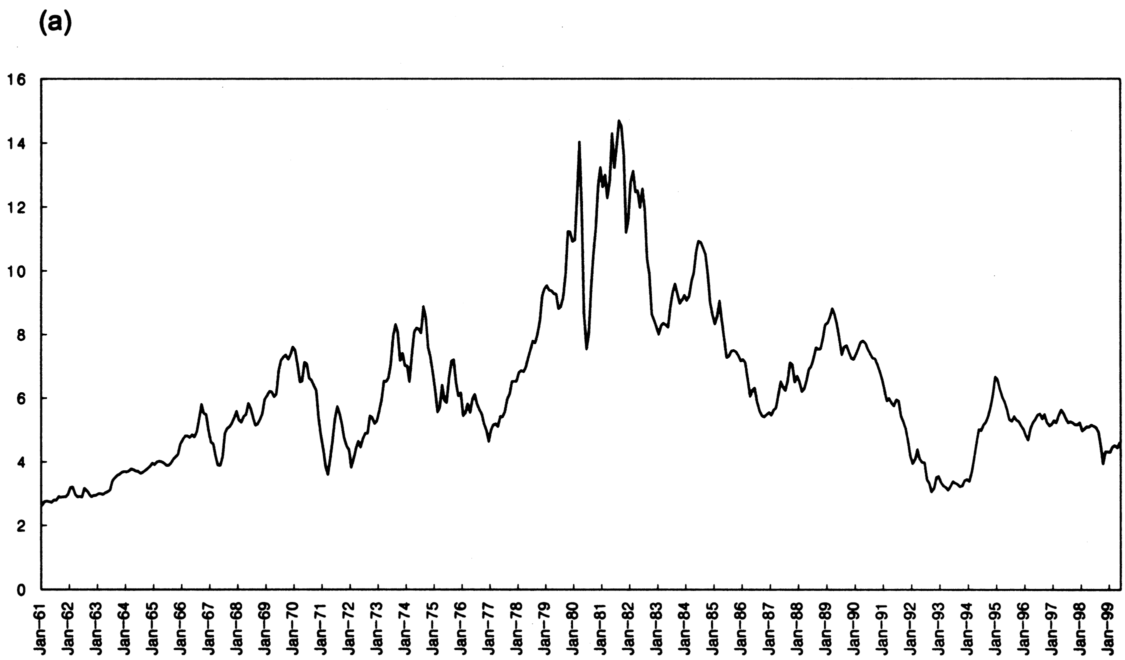
In this study, input variables are selected based on Fisher's theory that nominal interest rates (i.e. monthly US

Table 2
Descriptive statistics of the US Treasury monthly yields from January 1977 to May 1999 (T-bill, Treasury bill rates; T-note, Treasury note rates; T-bond, Treasury bond rates)

| Statistics | Federal funds | 1-year T-bill | 3-year T-note | 5-year T-note | 10-year T-note | 30-year T-bond |
|---|---|---|---|---|---|---|
| Mean | 7.68 | 7.11 | 8.17 | 8.39 | 8.64 | 8.78 |
| Minimum | 2.92 | 3.06 | 4.17 | 4.18 | 4.53 | 5.01 |
| Maximum | 19.10 | 14.70 | 16.22 | 15.93 | 15.32 | 14.68 |
| Range | 16.18 | 11.64 | 12.05 | 11.75 | 10.79 | 9.67 |
| Median | 6.85 | 6.58 | 7.73 | 7.85 | 8.11 | 8.27 |
| Lower quantile | 5.40 | 5.23 | 6.07 | 6.40 | 6.80 | 7.27 |
| Upper quantile | 9.35 | 8.58 | 9.47 | 9.76 | 10.28 | 10.33 |
| Quantile range | 3.96 | 3.35 | 3.40 | 3.36 | 3.48 | 3.06 |
| Variance | 11.83 | 6.89 | 7.54 | 6.87 | 6.10 | 5.07 |
| Standard deviation | 3.44 | 2.63 | 2.75 | 2.62 | 2.47 | 2.25 |
| Standard Error | 0.21 | 0.16 | 0.17 | 0.16 | 0.15 | 0.14 |
| Skewness | 1.23 | 0.82 | 0.84 | 0.82 | 0.74 | 0.73 |
| Kurtosis | 1.55 | 0.17 | 0.09 | −0.03 | −0.21 | −0.25 |

Table 3
Pearson correlation matrix of the US Treasury monthly yields from January 1977 to May 1999

| | Federal Funds | 1-year T-bill | 3-year T-note | 5-year T-note | 10-year T-note | 30-year T-bond |
|---|---|---|---|---|---|---|
| Federal funds | 1.0000 | | | | | |
| 1-year T-bill | 0.9735 | 1.0000 | | | | |
| 3-year T-note | 0.9314 | 0.9798 | 1.0000 | | | |
| 5-year T-note | 0.9021 | 0.9578 | 0.9951 | 1.0000 | | |
| 10-year T-note | 0.8674 | 0.9286 | 0.9810 | 0.9949 | 1.0000 | |
| 30-year T-bond | 0.8374 | 0.9015 | 0.9644 | 0.9849 | 0.9968 | 1.0000 |



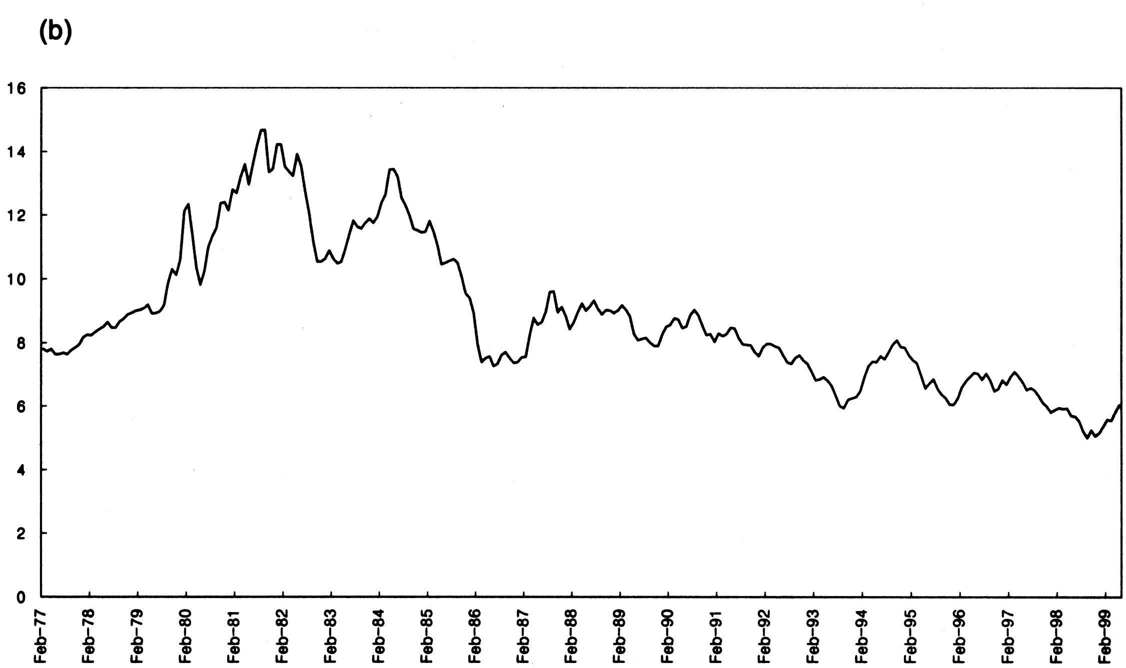




Fig. 3. (a) US Treasury bills with a maturity of 1 year from January 1960 to May 1999. (b) US Treasury bonds with a maturity of 30 years from January 1977 to May 1999.

Table 4
Period and descriptive statistics of groups for the training phase, January 1961–August 1991 in 1-year bills and January 1977–December 1994 in 30-year T-bonds

| | Group 1 | Group 2 | Group 3 | Group 4 |
|---|---|---|---|---|
| *1-year T-bills* | | | | |
| Periods | January 61–November 65 | December 65–February 73 | March 73–May 78 | June 78–August 91 |
| Minimum | 2.720 | 3.600 | 4.640 | 5.260 |
| Maximum | 4.230 | 7.610 | 8.880 | 14.700 |
| Range | 1.510 | 4.010 | 4.240 | 9.440 |
| Mean | 3.378 | 5.419 | 6.507 | 8.654 |
| Variance | 0.219 | 0.938 | 1.008 | 5.240 |
| Standard deviation | 0.468 | 0.969 | 1.004 | 2.289 |
| Skewness | 0.147 | 0.496 | 0.363 | 0.781 |
| Kurtosis | −1.544 | −0.361 | −0.575 | −0.135 |
| *30-year T-bonds* | | | | |
| | Group 1 | Group 2 | | |
| Periods | January 77–February 86 | March 86–December 94 | | |
| Minimum | 7.640 | 5.940 | | |
| Maximum | 14.680 | 9.610 | | |
| Range | 7.040 | 3.670 | | |
| Mean | 10.819 | 7.995 | | |
| Variance | 3.862 | 0.676 | | |
| Standard deviation | 1.965 | 0.822 | | |
| Skewness | 0.011 | −0.365 | | |
| Kurtosis | −1.062 | −0.262 | | |

Treasury security rates) consist of expected real interest rates and anticipated inflation:

$$\text{Nominal Interest Rates} = \text{Expected Real Interest Rates} + \text{Anticipated Inflation}$$

Many econometricians have conducted the research upon this Fisher-type interest rate equation (Darby, 1975; Feldstein, 1976; Makin, 1983; Mundell, 1963; Tanzi, 1980; Tobin, 1965). They have explained the impact of anticipated inflation on nominal interest rates. Moreover, they have investigated the relationship of money surprise and real GNP growth for the Fisher-type interest rate equation. These relationships are summarized in Fig. 2. In Fig. 2, the straight line is meant to have more causal effects than the dotted line. The causal model like Fig. 2 presents an explanation which would clarify the results (Kim & Park, 1996).

The input data sets in this study consist of the figures for the monthly rate of change. Given the data sequence $d_1, d_2, \ldots, d_t$, we form the rate of change at time $t+1$ by dividing the first difference at that time by the datum at time $t$:

$$\frac{d_{t+1} - d_t}{d_t} \tag{4}$$

The input variables included in this model are anticipated inflation, expected real interest rates, money surprise and real GNP growth which are shown in Fig. 2. The rate of change of the consumer price index is used as a measure for the anticipated inflation while the expected real interest rates is calculated as the difference between the nominal interest rates and the anticipated inflation at time $t$ according to the Fisher-type interest rate equation. M2 and industrial production index are added to input variables as a measure for money surprise and real GNP growth, respectively. The list of input variables used in this study is summarized in Table 1.

The data used in this study is monthly yields on the US Treasury securities from January 1977 to May 1999. As a starting point, we compute descriptive statistics including basic statistics and Pearson correlations among securities. Table 2 shows that the mean and the median change in proportion to maturity. In Table 3, computation on the monthly yields shows that the Pearson correlation between 1-year T-bills and 30-year T-bonds is relatively small except the Federal Funds; The correlation between 1-year T-bills and 3-year T-notes is 0.97; between 1-year T-bills and 5-year T-notes, 0.95; between 1-year T-bills and 10-year T-notes, 0.92; and between 1-year T-bills and 30-year T-bonds, 0.90. Thus, the forecast of the US Treasury security rates had better not be based on the equivalence alone, but should be performed through individual modeling. In this sense, we build two integrated neural network models for 1-year T-bills and 30-year T-bonds, and establish the experiment interval differently for each model. The motivation for this plan is to see the impact of interval size on the performance and further, to demonstrate the generality of the proposed model.

For 1-year T-bills, the training phase involves observations from January 1961 to August 1991 and the testing phase runs from September 1991 to May 1999. For 30-year T-bonds, the training phase runs from January 1977 to December 1994 and the testing phase runs from January 1995 to May 1999. The interest rates data is presented in

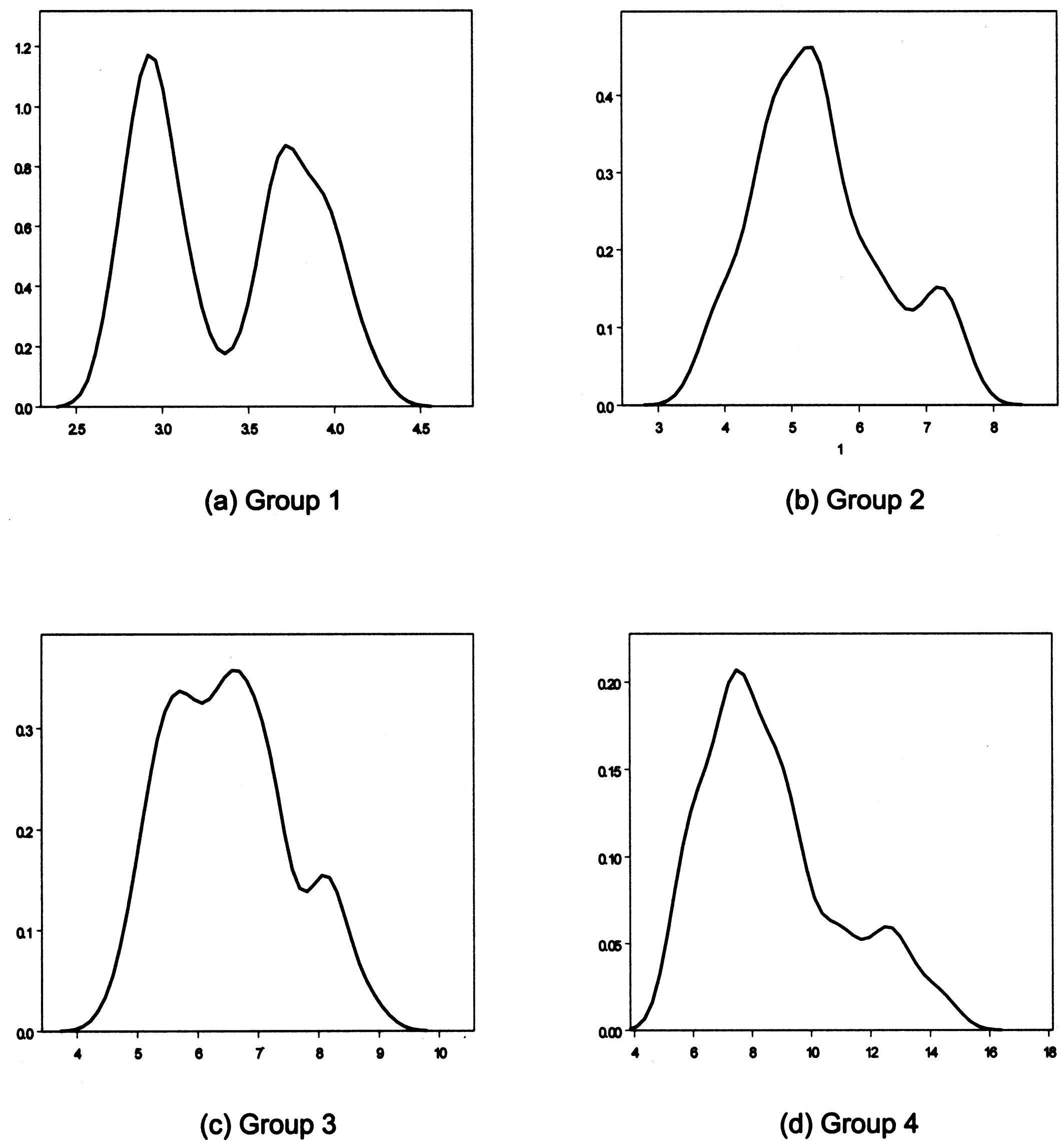



Fig. 4. Density plot of four homogeneous groups for 1-year T-bills.

Fig. 3. Fig. 3 shows that the movement of interest rates fluctuates highly in both 1-year T-bills and 30-year T-bonds.

The study employs two neural network models. One model, labeled Pure_NN, involves four input variables at time $t$ to generate a forecast for $t + 1$. The input variables are M2, CPI, ERIR and IPI. The second type, labeled BPN_NN, is the two-step BPN model that consists of three stages mentioned in Section 3. The first step is the CPGD stage that forecasts the change-point group while the next step is the OFNN stage that forecasts the output. For validation, two learning models are also compared.

## 5. Empirical results

The Pettitt test is applied to the interest rates dataset. As the interest dataset is about forty years long for 1-year T-bills, it is considered that there exist two or more change points. It is further assumed that there exists just one change point because of the small size of data for 30-year T-bonds. Table 4 shows these results for 1-year T-bills and 30-year T-bonds.

For the case of 1-year T-bills, Table 4 also presents descriptive statistics including the mean and the variance. Group 1 is the stable interval that has small variance. Groups 2 and 3 have more fluctuated intervals than Group 1 in terms of the variance. Group 4 fluctuates highly. The values of skewness and kurtosis indicate that the four groups have similar attributes in distribution. Fig. 4 depicts the density plot for each group. By Fig. 4, Groups 2 and 4 are considered to have similar distribution in terms of the shape.

In the case of 30-year T-bonds, Table 4 shows that Group 2 is the stable interval with small variance while Group 1 fluctuates heavily with a big range. Fig. 5 presents the

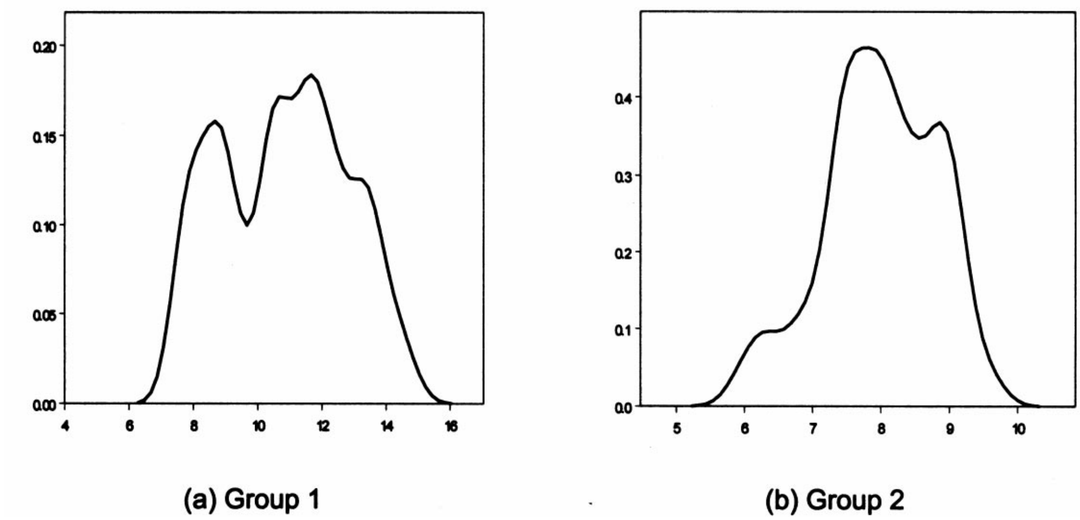



Fig. 5. Density plot of two homogeneous groups for 30-year T-bonds.

density plot for each group. Through Fig. 5, Groups 1 and 2 are recognized to have the distinctive distribution.

To highlight the performance of the models, the actual values of interest rates and their predicted values are shown in Fig. 6. For 1-year T-bills, the predicted values of the pure BPN model (i.e. Pure_NN) move apart from the actual values in some intervals. In the case of 30-year T-bonds, the predictive values of the proposed model also come closer to the actual values than those of the pure BPN model for the most intervals.

Numerical values for the performance metrics by the predictive model are given in Table 5. Fig. 7 presents histograms of RMSE, MAE and MAPE for the forecast of each learning model in the cases of 1-year T-bills and 30-year T-bonds. According to RMSE, MAE and MAPE, the outcomes indicate that the proposed neural network model is superior to the pure BPN model for both of the interest rates.

We use the pairwise *t*-test to examine whether the differences exist in the predicted values of models according to the absolute percentage error (APE). This metric is chosen because it is commonly used (Carbone & Armstrong, 1982) and is highly robust (Armstrong & Collopy, 1992; Makridakis, 1993). As the forecasts are not statistically independent and not always normally distributed, we compare the APEs of forecast using the pairwise *t*-test. Where sample sizes are reasonably large, this test is robust to the distribution of the data, to nonhomogeneity of variances, and to statistical dependence (Iman & Conover, 1983). Table 6 shows *t*-values and *p*-values. The neural network models using change-point detection perform significantly better than the pure BPN model at a 1% significant level. Therefore, the proposed model is demonstrated to obtain improved performance using the change-point detection approach.

In summary, the neural network models using the change-point detection turns out to have a high potential in interest rates forecasting. This is attributable to the fact that it categorizes the interest rates data into homogeneous groups and extracts regularities from each homogeneous group. Therefore, the neural network models using change-point detection can cope with the noise or irregularities more efficiently than the pure BPN model.

## 6. Concluding remarks

This study has suggested change-point detection to support neural network models in interest rates forecasting. The basic concept of this proposed model is to obtain significant intervals divided by the change points, to identify them

Table 5
Performance results of rate forecasting based on the root mean squared error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE)

| Model | RMSE | MAE | MAPE (%) |
|---|---|---|---|
| *1-year T-bills* | | | |
| Pure_NN | 0.0973 | 0.2506 | 5.969 |
| BPN_NN | 0.0584 | 0.1745 | 3.746 |
| *30-year T-bonds* | | | |
| Pure_NN | 2.5462 | 1.4976 | 24.828 |
| BPN_NN | 1.7553 | 1.2668 | 20.836 |

Table 6
Pairwise *t*-tests for the difference in residuals between the pure BPN model and the proposed neural network model for 1-year T-bills and 30-year T-bonds based on the absolute percentage error (APE) with the significance level in parentheses (***significant at 1%)

| Interest rates | Test value |
|---|---|
| 1-year T-bills | 3.43 (0.000)*** |
| 30-year T-bonds | 8.17 (0.000)*** |

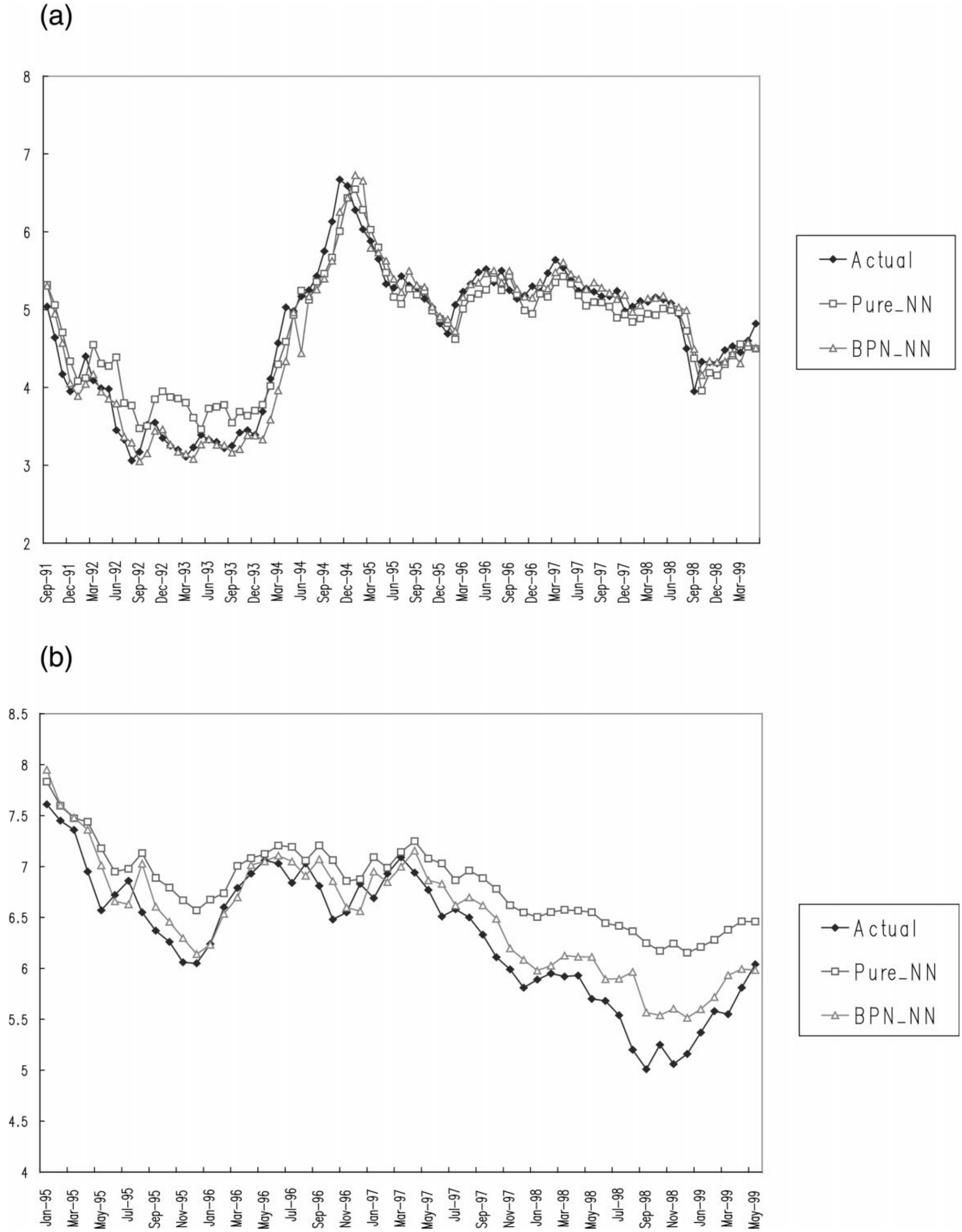
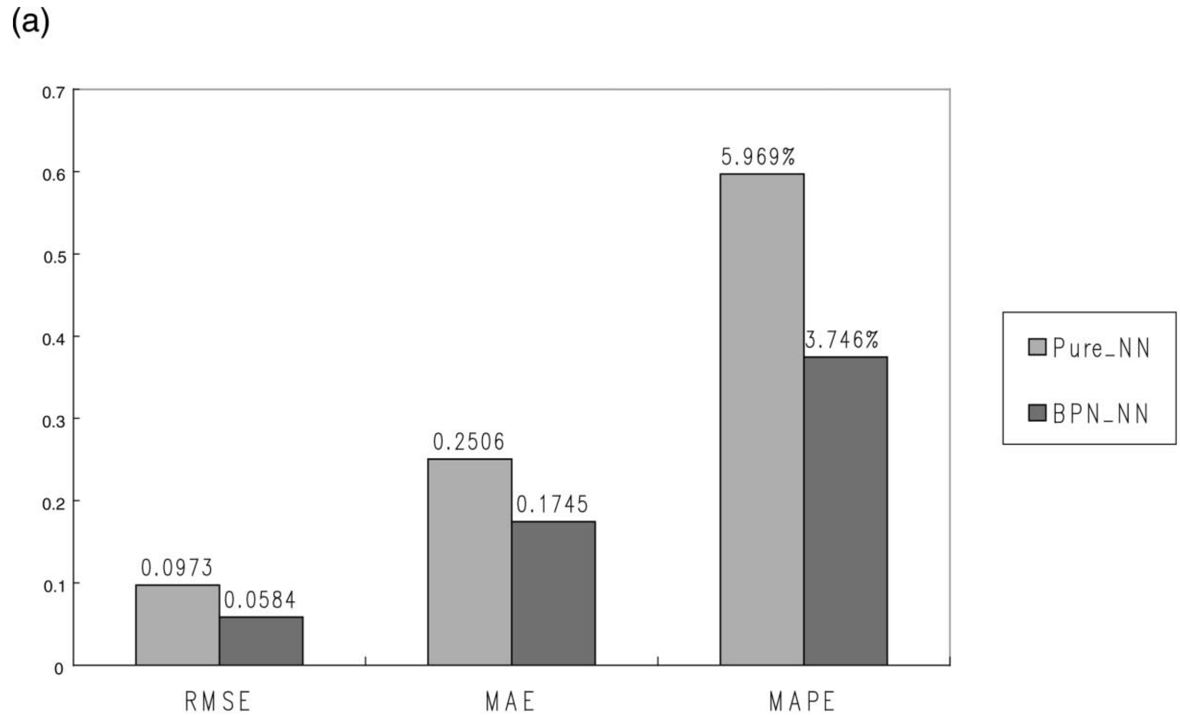



Fig. 6. (a) Actual vs predicted values due to the models for 1-year T-bills. (b) Actual vs predicted values due to the models for 30-year T-bonds.

as change-point groups, and to use them in interest rates forecasting. We propose the integrated neural network model that consists of three stages. In the first stage, we conduct the nonparametric statistical test to construct the homogeneous groups. In the second stage, we apply BPN to forecast the change-point group. In the final stage, we also apply BPN to forecast the output.

The neural network models using change-point detection perform significantly better than the pure BPN model at a 1% significant level. These experimental results imply the change-point detection has a high potential to improve the performance. Our integrated neural network model is demonstrated to be a useful intelligent data analysis method with the concept of



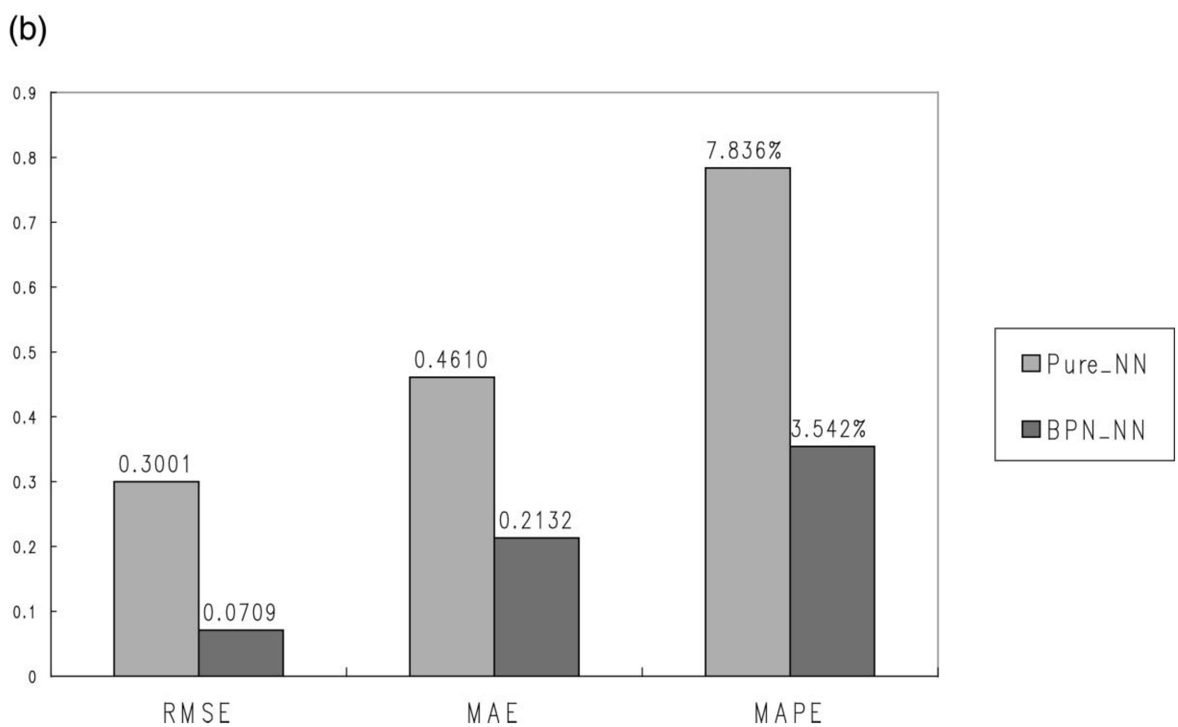




Fig. 7. (a) Histogram of RMSE, MAE and MAPE resulting from forecasts of 1-year T-bills. (b) Histogram of RMSE, MAE and MAPE resulting from forecasts of 30-year T-bonds.

change-point detection. In conclusion, we have shown that the proposed model improves the predictability of interest rates significantly.

The proposed model has the promising possibility of improving the performance if further studies are to focus on the optimal decision of the number of change point and the various approaches in the construction of change-point groups. In the OFNN stage, other intelligent techniques besides BPN can be used to forecast the output. In addition, the proposed model may be applied to other chaotic time series data such as stock market prediction and exchange rate prediction.

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