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Modeling Federal Funds rates: a comparison of four methodologies

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Abstract Monthly Federal Fund interest rate values, set by the Federal Open Market Committee, have been the subject of much speculation prior to the announcement of their new values each period. In this study we use four competing methodologies to model and forecast the behavior of these short term Federal Fund interest rates. These methodologies are: time series, Taylor, econometric and neural network. The time series forecasts use only past values of Federal Funds rates. The celebrated Taylor rule methodology theorizes that the Federal Fund rate values are influenced solely by deviations from a desired level of inflation and from potential output. The econometric and neural network models have inputs used by both the time series and Taylor rule. Using monthly data from 1958 to the end of 2005 we distinguish between sample and out-of-sample sets to train, evaluate, and compare the models' effectiveness. Our results indicate that the econometric modeling performs better than the other approaches when the data are divided into two sets of pre-Greenspan and Greenspan periods. However, when the data sample is divided into three groups of low, medium and high Federal Funds, the neural network approach does best.

Keywords Federal Funds · Modeling interest rates · Taylor rule · Neural networks

1 Introduction

The key instrument used by the Federal Reserve (Fed) to implement its monetary policy is the short-term interest rate called the Federal Funds rate (Fed Funds). These rates are announced by the Federal Open Market Committee (the FOMC) after a closed door meeting and influence rates around the world. Fed watchers carefully analyze the decisions made by the Fed in order to anticipate the Fed's future moves to increase, decrease or leave unchanged the Fed Funds. Numerous methodologies have been developed to both model and forecast Fed Funds. For an account of some of the methodologies that have been applied, see [5, 14].

The basic purpose of this paper is to evaluate the forecasting performance of monthly Federal Funds rates using several competing methodologies. Rather than considering every available method, we shall restrict ourselves to the following four approaches: (1) a time series model where Fed Funds rates are determined solely by past rates; (2) the Taylor model where Fed Funds are functions of past influential factors; (3) an econometric model where Fed Funds are functions of past rates as well as influential factors, and (4) a neural network model using the same input variables as the econometric model. A chart indicating the monthly path of the Fed Funds rates from 1957 through 2005 is shown in Fig. 1.

Sections 2 through 5 discuss each of these methodologies in detail. The data sets used for the models are

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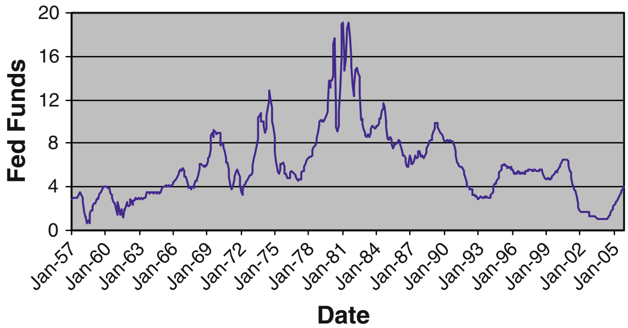

Fig. 1 Monthly Federal Funds rates from 1957 through 2005

elaborated in Sect. 6. The results from each of the models and the results from applying these models to a test set are discussed in Sects. 7 and 8, respectively. Lastly, in Sect. 9, conclusions from applying the models to the data sets are listed.

2 Time series model: Fed Funds as random walks

The time series model assumes that it is possible to forecast the interest rate using only the previous term interest rate as a variable input. Much research has been conducted using a continuous-time short-term interest rate model specification of a diffusion process such as

$$dr = (\alpha + \beta r)dt + \sigma r^{\gamma} dz \tag{1}$$

where:

r short-term interest rate
α, β, γ model coefficients to be determined
σ standard deviation of the short-term rates
z Brownian motion

This formulation assumes that movements in interest rates are strictly a function of interest rate levels, volatility and noise. For investigations of such formulations, see [2]. From (1), a discrete random walk time series model can be obtained:

$$r_t = \alpha + \beta r_{t-1} + \varepsilon_t \tag{2}$$

where:

r_t short-term interest rate at time t,
r_{t-1} short-term interest rate at time $t-1$,
ε_t model error term at time t with $E(\varepsilon_t) = 0$ and a certain variance,
α, β model coefficients to be determined

Depending on the date range evaluated, the value of β is normally found to be very significant and close to 1. This indicates that interest rates have high serial correlation. Such a result is to be expected since, on average, interest rates are only changed at most monthly by the Fed. In the sections that follow, the model described in (2) will be used as a base model on which to evaluate the effectiveness of other models. Figure 2 shows the relationship between Fed Funds at time $t-1$ and time t, sorted by funds at $t-1$ for the time period of our data set. Notice the close to linear relationship for all but the highest values on the figure.

3 The Taylor model: interest rates are functions of past influential factors

The most famous Fed Funds model is the one proposed by Taylor [15] and further evaluated in Taylor [16] and Kozicki [8]. Taylor argued that a central bank tries to keep the economy in equilibrium with inflation at about 2% and output at a sustainable potential level. Taylor fitted a regression model explaining Fed Funds as a dependent variable of certain important macroeconomic variables measuring the rate of inflation and the deviation of total output from its potential. Woodford [19] named the statistical model proposed by Taylor as the Taylor rule and also demonstrated that it can be derived analytically from a stylized Keynesian macroeconomic model. The Taylor rule argues that Fed Funds are determined by the Fed's objectives to promote price stability and economic growth. Thus, the future value of the Fed Funds rate is based only on the values of the current rate of inflation and the level of unemployment and the equation coefficients are specified. There is both a quarterly and monthly version. We concentrate on the monthly version where:

$$r_t = 2 + p_{t-1} + 0.5(p_{t-1} - 2) + 0.5(u_{t-1} - 4) \tag{3}$$

where:

r_t Fed Funds rate at t,
p_{t-1} lagged monthly inflation measured by CPI,
u_{t-1} lagged monthly unemployment rate

By rearranging terms, this equation can also be written as:

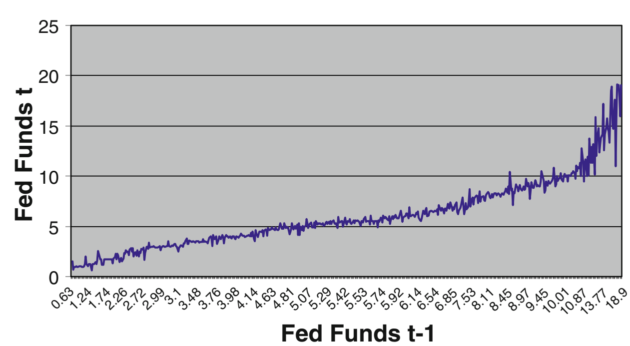

Fig. 2 Fed Funds at time $t-1$ versus at time t

$$r_t = 1 + 1.5p_{t-1} + 0.5(u_{t-1} - 4) \tag{4}$$

Note that this second formulation of the equation indicates that the Federal Funds rate should be changed 1.5 percent for each 1 percent change in inflation. It is felt that such a forceful reaction to inflation tends to drive future inflation to a lower value. Judd and Rudebusch [6] show that when interest rates are not adjusted strongly in reaction to past inflation, the result can be rampant future inflation similar to the inflation exhibited during the era of 1970–1978. The last term focuses on the difference of the unemployment rate from an acceptable level of 4% and indicates that the rate should be adjusted one-half of one percent for each one percent change of the unemployment rate. Values of $(u_{t-1} - 4)$ are referred to as excess unemployment.

Bernanke [1] has revisited this important issue and has argued that an inflation coefficient that is around 1.5 sends a strong signal to market participants that the Fed is committed to fighting inflation vigorously. This in turn moderates inflation expectations that play an important role to moderating actual inflation.

The Taylor rule has become the basis for comparison and development of other policy reaction functions. Modifications to the Taylor rule include the addition of other variables as exemplified by Clarida et al. [3]. Other considerations include the use of real-time data and the addition of expectations of future values of inflation and output, as shown in Orphanides [11, 12]. Actually since the original formulation by Taylor [15], economists have modified the rule in a number of ways. A list of some of these modifications can be found in Fernandez and Nikotsko-Rzhevskyy [4].

Figures 3 and 4 show the paths of the two variables used in the Taylor equation (4), that is, Unemployment Rate and inflation as measured by the Consumer Price Index Change.

The relationship of these two variables to the future Federal Funds rate can be seen in Figs. 5 and 6 where each

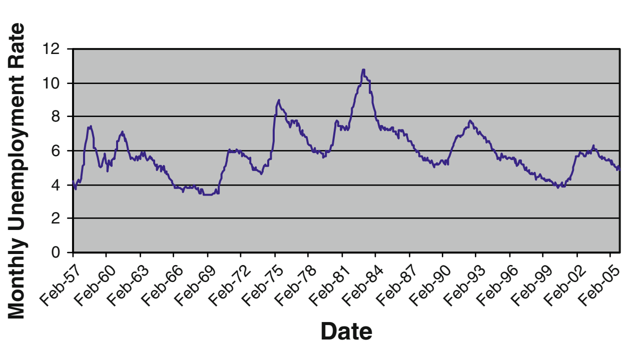

Fig. 3 Unemployment rate

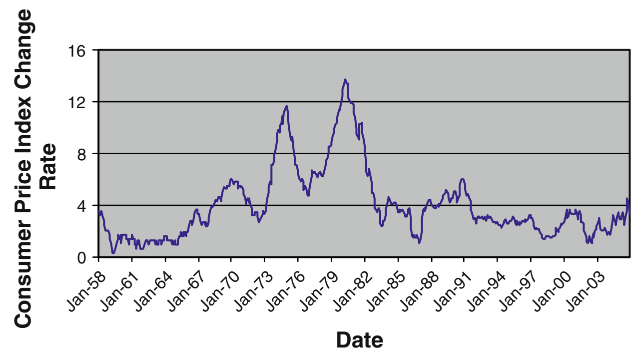

Fig. 4 CPI monthly change rate

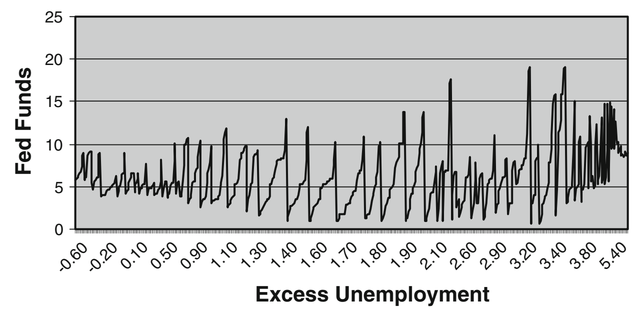

Fig. 5 Excess unemployment at $t - 1$ versus Fed Funds at t

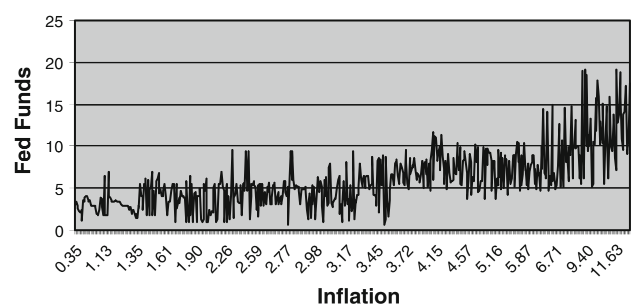

Fig. 6 Inflation at $t - 1$ versus Fed Funds at t

variable at $t - 1$ is shown versus the Federal Funds rate at time t.

4 The econometric model: interest rates are functions of past rates as well as influential factors

The third approach combines the two factors of the Taylor rule with previous interest rates, that is, with the time series model. In other words, this approach combines the random walk and the Taylor model. Some authors call this an extended Taylor rule while others also interpret it as a variation of the Taylor model. By combining (2) and (3), we obtain the following using slightly different coefficient symbols:

$$r_t = \alpha + \rho r_{t-1} + \beta(p_{t-1} - 2) + \lambda(u_{t-1} - 4) + \varepsilon_t \quad (5)$$

where:

r_t	short-term interest rate at time t
p_{t-1}	inflation rate at time $t-1$,
$u_{t-1} - 4$	excess unemployment,
ε_t	model error term at time t with $E(\varepsilon_t) = 0$ and a certain variance,
$\alpha,\ \beta,\ \lambda,\ \rho$	model coefficients to be determined

Numerous investigators have evaluated equations of this form using past values of inflation and excess unemployment for various time intervals and various countries including Judd and Rudebusch [6], and Clarida et al. [3]. We observe that our econometric model is just a one equation model. Obviously, numerous multiple equation macroeconometric models have been developed, the most famous one being the Fed model. For a brief review of this model and its forecasting performance, see [17]. These authors document that when large macroeconometric models are built and used to assist in policy formulations the high degree of model uncertainty undermines the performance of such models.

5 Interest rates can be determined by a neural network using past rates and influential factors

Neural networks have shown much promise in various financial applications, especially with complex problems [9, 13, 18]. With hidden layers, a neural network can be a non-linear estimator that uses weighted interconnected nodes to generate a forecast. It is very dependent upon the training data set since it adjusts its weights to optimize performance on this training data. The final set of weights which comprises the trained network is then used to forecast values for new data. This approach has the ability to often outperform linear models on complex data sets.

Neural networks for this study were run using the SPSS data mining package Clementine. According to KDNuggets [7], the association for knowledge discovery and data mining, Clementine was the most used commercial data mining software in 2007. Clementine allows the user to determine a number of settings for running the neural network, but has a very friendly interface for the business user with drag and drop nodes used for setting up and running the model. The choices for changes to the built-in model available to the user are shown in the Figs. 7 and 8. While training, the neural network holds out a specified randomly selected portion of the data set that it uses to periodically check network performance on new data. In this case, 80% of the data was used for training, with 20% used in order to prevent overtraining.

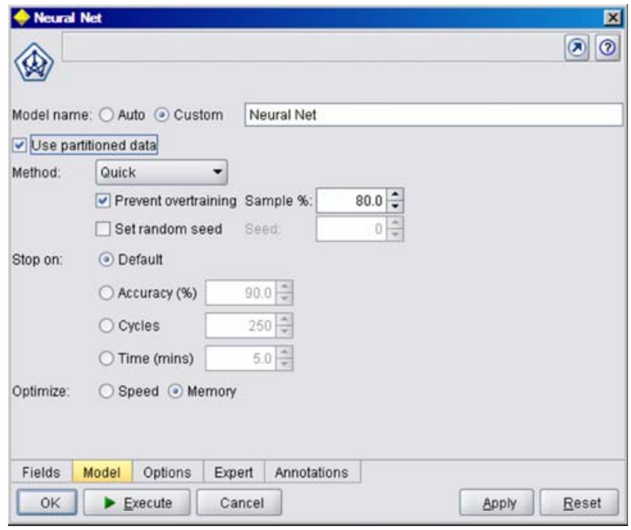

Fig. 7 SPSS Clementine neural network model settings

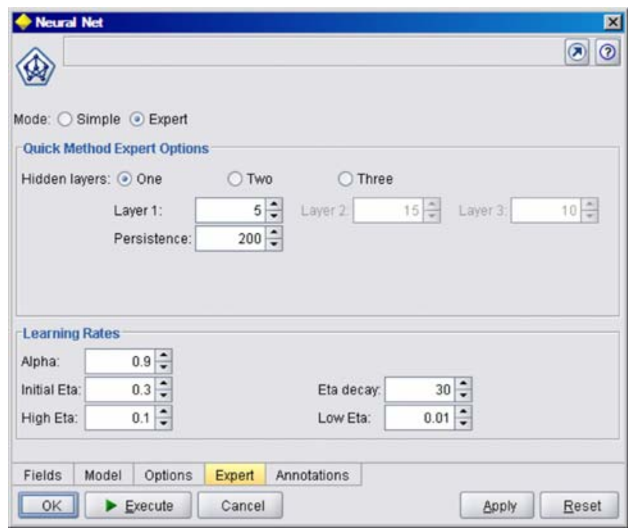

Fig. 8 SPSS Clementine neural network expert settings

The network this model uses contains three layers. The input layer has one node corresponding to each input variable. These inputs, as with the econometric model, are the previous Fed Funds rate, inflation as measured by the CPI, and excess unemployment. The output layer has one node, the forecasted variable, Fed Funds rate.

In between these input and output layers is a hidden layer. The hidden layer is a set of nodes with no direct variable interpretation, but which serves to help mold the form of the inputs to the output. Each input and hidden layer node is multiplied by a weight that adjusts the importance of the node. In this model, we tried a variety of topologies. Both 1 and 2 hidden layers with from 3 to 9 nodes were run. The network needed at least five nodes in one hidden layer in order to forecast well. Though the

Clementine settings allow for up to three hidden layers, the additional layers and nodes did not significantly improve the performance. Thus, we used the smallest network that yielded acceptable results on most of the data, one hidden layer with five nodes.

Once the topology was finalized, the network was set to train a final time on the data set. In Clementine, the network continues to train, if no improvement is seen, for the number of cycles set in the Persistence option. The set of weights that performs optimally on both pieces of the training data set, the 80% and the 20%, is used as the final network weight set.

6 Data

There are multiple ways to get a measure of inflation. We use inflation measured by the CPI, monthly data for Fed Funds, and unemployment from January 1957 to December 2005. CPI data is annualized by calculating $\ln(x_t/x_{t-12}) \times 100$ for each month. Percentages are adjusted to whole numbers, for example, 4% is used as 4, not 0.04. In the Econometric and Neural Network models, we calculate an "Adjusted CPI" found by subtracting 2 from the above number (the form in which inflation occurs in the general econometric equation). In addition, monthly data for Federal Funds rates and unemployment rates from January 1957 to December 2005 are used. The variable "Excess" was calculated as the Unemployment Rate minus 4. That is, it measures how far the Unemployment Rate varies from this critical value.

The computations for each model are performed for various subsamples of the set. These subsamples are divided first into two distinct time periods, then into three sets by value of the current Fed Funds rate. The first two subsamples are split based on the time that Alan Greenspan was appointed chairman of the Fed. Since the Taylor formulation came into existence after Greenspan became the chairman of the Federal Reserve Board, we divided the data set into the time before Greenspan held this office, and the time during his tenure.

The data is then recombined and split into three groups based on the value of the Fed Funds rate at time $t - 1$. The values used to split the data into these subsamples are five and ten.

Specifically, these five sets include: time prior to Greenspan (1957 through July 1987), since Greenspan (August 1987 through November 2005), the months where the Fed Funds rate at time $t - 1$ was less than 5 (low), between 5 and 10 (medium), and greater than 10 (high). The resulting data sets can be seen in Figs. 9 and 10.

For each subsample, a random set of 10% of the rows was held out from training and used as the test set. The models are all compared by looking at their performance on these five test sets. Sizes of each of the model training and test sets are shown in Table 1. The test sets contain a wide range of data values and can be seen in Figs. 11 and 12.

As explained in prior sections, not all variables are used in all models. The random walk model uses only the current Fed Funds number as an independent variable. The Taylor model uses CPI and Unemployment Rate. The Econometric and Neural Network models use Fed Funds, CPI, and Unemployment Rate all at month $t - 1$. The dependent variable for all models is Fed Funds at month t.

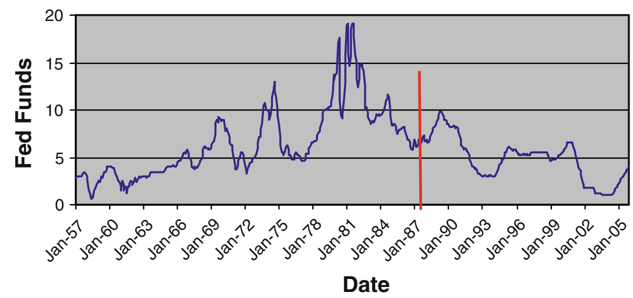

Fig. 9 Data set division based on Greenspan

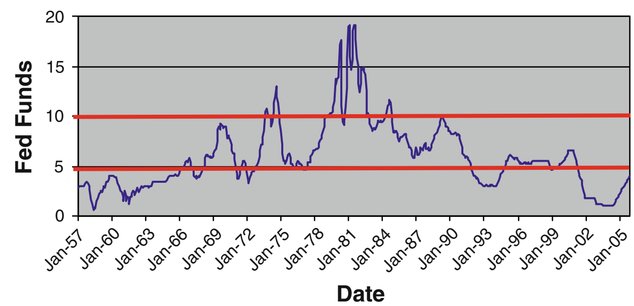

Fig. 10 Data set division based on size of rate

Table 1 Data set sizes

Data set	Training	Test	Total
Pre-Greenspan	319	36	355
Greenspan	197	22	219
r_{t-1}: 0–5	219	24	243
r_{t-1}: 5.01–10	243	27	270
r_{t-1}: over 10	55	6	61

7 Model results

On the random walk model, Table 2 shows the model-generated values for the intercept and coefficient on each data set. On all but one set, the coefficient was almost 1, as expected, and statistically significant (t-statistics are not

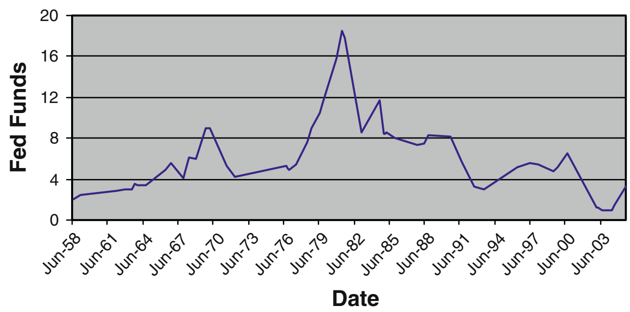

Fig. 11 Test sets for pre-Greenspan and Greenspan data sets

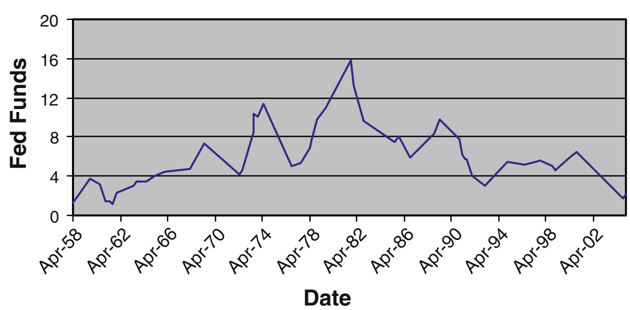

Fig. 12 Test sets for low, medium, and high data sets

Table 2 Random walk equation values across data sets

	Pre-Gr.	Gr.	High	Med.	Low
Intercept	0.177	0.006	1.48	0.021	0.02
Coefficient of r_{t-1}	0.973	0.995	0.88	0.995	1

Table 3 Values generated from the Taylor model across data sets

	PreGreenspan	Greenspan	High	Medium	Low
Intercept	2.334	1.797	5.005	5.755	2.837
Adj. CPI	0.789	1.477	0.564	0.197	0.496
Excess unemp.	0.296	−0.935	0.91	0.161	−0.49

reported). On the High set, it dropped to 0.879 and the intercept increased greatly.

Table 3 contains the coefficients generated by the Taylor model for the five data sets. It confirms the two predictions of model coefficients. The Excess Unemployment coefficient is always negative and small, indicating a dampening effect of excess unemployment. As excess unemployment grows past 4, Fed Funds decrease. The intercept values calculated for each of the data sets range from 0.007 to 1.442 while the Adjusted CPI is sometimes positive and sometimes negative. For the Greenspan period we get a coefficient for the Adjusted CPI of 1.477 which is very close to 1.5 hypothesized in (4). Other authors such as Mehra and Minton [10] have also confirmed that the Taylor rule describes well the Greenspan era.

Table 4 Values generated from the econometric model across data sets

	PreGreenspan	Greenspan	High	Medium	Low
Intercept	0.291	0.047	1.442	0.007	0.125
Fed funds	0.965	0.994	0.862	1.002	0.983
Adj. CPI	0.019	−0.007	0.066	−0.003	0.018
Excess unemp.	−0.035	−0.024	−0.027	−0.019	−0.022

Table 4 contains the coefficients generated by the Econometric model for the five data sets. It shows only two consistencies among the model coefficients. The Fed Funds rate coefficient is near 1 in all cases, and the excess coefficient is always negative and small, indicating a dampening effect of excess unemployment. As excess unemployment grows past 4, Fed Funds decrease.

The intercept values calculated for each of the data sets range from 0.007 to 1.442 while the Adjusted CPI is sometimes positive and sometimes negative. This model captures the significant role of the past Federal Funds rates in determining future ones since traditionally the Federal Reserve follows gradual changes in Fed Funds.

Table 5 reports the order of significance of the variables as used by the neural networks. In four of the five data sets, the Fed Funds rate is the most significant variable. However, during times when the current rate is High, the variable significance shifts and Fed Funds becomes the least important of the variables.

In these models, we see that the splitting of data has given us significantly different variable importance. There is no one model formulation that works equally well across all the data. However you decide to split the data, doing so will enable you to approximate the set better.

8 Model results on test sets

The mean squared error was calculated for each of the five models tested over each of the five subsets of data. The training and test sets were disjoint. Results show the lowest error amounts came from the models using all three of the variables for input. That is, in each subset of data, the lowest error came from either the Econometric or Neural Network model. More information enabled the models to approximate the target more effectively. The random walk model was very close to the lowest error in each subset, but never was the lowest. The Taylor model has significantly greater errors than any of the other three, over all data

Table 5 Order of variable significance in neural networks

	PreGreenspan	Greenspan	Low	Medium	High
Most important	Fed funds	Fed funds	Fed funds	Fed funds	CPI
	Excess unEmp.	CPI	CPI	CPI	Excess unemp.
Least important	CPI	Excess unemp.	Excess unemp.	Excess unemp.	Fed funds

Table 6 Mean squared error comparisons on test sets

Model/data set	Pre-Green	Greenspan	High	Med.	Low
Random walk	0.676	0.034	0.574	0.271	0.122
Taylor	10.036	8.392	16.754	9.701	6.651
Econometric	**0.657**	**0.030**	0.613	**0.262**	0.124
Neural network	1.121	0.130	**0.372**	0.269	**0.100**

subsets. The results are shown in Table 6 with the lowest error in bold.

Notice, in the results from Table 6, we see that the Neural Network was not the best model when the data was split simply by time period. However, when the data was split by type based on current Fed Funds level, the Neural Network outperformed the random walk each time, and in two of the three sets, was best overall.

9 Conclusions

This paper has reviewed four methods for modeling the behavior of Federal Funds. They are the standard random walk, the Taylor rule, an econometric model that relates the Federal Funds to fundamental variables including past values of Federal Funds and also the neural network approach. Using monthly data from 1958 to 2005 of several important macroeconomic variables, the results show that the econometric modeling performs better than the other approaches when the data are divided into two sets of pre-Greenspan and Greenspan. However, when the data sample is divided into three groups of low, medium and high Federal Funds, the neural network approach does best. Actually, the neural network approach does best at the extreme sets of high and low interest rates, while the methodology based on econometric modeling performs best in the mid-range of interest rates. This is the range of interest rates between 5% and 10%. In fact the neural networks identify inflation as measured monthly by the CPI as the most relevant variable during the high Fed Funds sample that has an appealing intuitive explanation. It is precisely during periods of very high inflation that the Federal Reserve increases Fed Funds both to reduce current inflation but more importantly to reduce future inflationary expectations. In such periods of very high inflation the role of unemployment becomes secondary to inflation. In other words, since the Fed cannot simultaneously reduce inflation and promote growth, it often assesses the risks of inflation versus the risks of an economic slowdown and targets the high risks economic variable. Obviously when inflation is very high, the risks associated with this high inflation receive more attention compared to the risks of an economic slowdown. The neural network has the advantage over the other models to identify inflation as the high risk variable in an environment of high Fed Funds.

The main conclusion of our work is that separating the data set into more homogeneous segments makes it possible to improve the predictive ability of the equations. When the split is based on the current value of the Fed Funds rate, then the neural network methodology outperforms both the random walk and the Taylor rule approaches. When the split is simply time-based, then the econometric model is the one to use. Our models also confirm that in the pre-Greenspan era, unemployment as a proxy for economic growth played a more important role in monetary policy, while since August 1987 when Greenspan was appointed Chairman of the Federal Reserve Board, inflation has become on average the targeted variable of Fed Funds policies.

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