Using an evolving criterion to assess the Federal Reserve's behaviour in recent years [*]

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1. Introduction

In recent years a large body of literature has investigated the central bank's behaviour in relation to the conduct of monetary policy. The two main approaches which dominated the scene are based, respectively, on: *i*) structural VAR models, an approach which aims to study the dynamic effects of identified monetary policy shocks on some key macroeconomic variables (see, e.g. Christiano, Eichenbaum and Evans 1999); *ii*) modeling the central bank's 'reaction function', i.e. estimating structural equations representing the response of the monetary policy instrument to changes in economic conditions. These changes, in turn, are synthesized by the variations of a small set of variables, usually a measure of aggregate economic activity such as the unemployment gap or, alternatively the output gap, and a measure of inflation (see, e.g. Clarida, Galí and Gertler 1998).

In this paper we take a different view on monetary policy and undertake an analysis, concerning the behaviour of the Federal Reserve for the period 1987-2002, which is based on neuro-fuzzy techniques. Our main goal is to shape the evolution of the federal funds rate, that is the evolution of the Fed's policy instrument. In general,

the neuro-fuzzy approach appears particularly useful in contexts of 'vague knowledge' about the economic system and, moreover, in situations characterized by the ability of economic units to learn from their experience. Indeed, both these aspects seem to characterize the action of a central bank and require a conduct of monetary policy founded on the adoption of flexible rules.

Let us suppose an economic system be characterized by a phase of 'low unemployment' (on passage: the economic situation faced by the Federal Reserve in the second half of the 1990s). Such a situation poses two separate questions: *i*) the economic interpretation of 'low unemployment'; *ii*) the implications for the conduct of monetary policy. Clearly, this is a typical context of vague knowledge ('low' with respect to what?) and moreover a situation in which the central bank needs to develop a process of learning about possible structural changes affecting the economic system which may have led to a permanent reduction in the unemployment rate. Thus, from the point of view of the central bank, it appears sensible to adopt flexible rules. Note that rules based on 'fuzzy' transformation of the variables in a small number of qualitative (linguistic) terms constitute one of the main features of the approach adopted in this paper.

It is worth pointing out that on a purely analytical ground some progress could be made by anchoring the notion of 'low unemployment' to a 'natural rate model', since in this case 'low' would identify a condition experienced by the economic system in which the observed rate of unemployment falls below the long-run natural rate, thus providing a signal for future increases of the inflation rate and inducing the raise of the short-term interest rate. Unfortunately, even by adopting this framework, the vagueness cannot be eliminated: it is simply shifted towards the unobservable notion of 'natural rate of unemployment'.[1]

This paper deals with a Sugeno fuzzy model in order to develop a systematic structure that generates fuzzy rules from a given input-output data set. The input data vector is given by the variables monitored by the Federal Reserve whereas the output is the monetary policy instrument. We assume that the following input variables be

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[1] Staiger, Stock and Watson (1997) provide a measure of the uncertainty about the NAIRU (non-accelerating inflation rate of unemployment) by estimating the standard errors associated with the estimation of the NAIRU itself. The conclusion they draw is that for the United States in the 90s the long-run equilibrium unemployment rate is between 4 and 8%.

monitored by the central bank: the rate of growth of industrial production, the unemployment rate, the rate of inflation measured by the consumer price index (CPI) and an index of the stock market. As far as the instrument is concerned, it is widely recognized that apart from the short experience of the period 1980-1982 when, under Volcker's leadership a monetary aggregate was adopted, thereafter the federal funds rate has represented the monetary policy instrument.

Thus, we consider a small set of real and nominal variables. Moreover, we include an indicator of the state of confidence of the stock market. Indeed, a recent strand of research has explored the role played by the stock market in shaping the evolution of monetary policy in the Greenspan era (see e.g. Rigobon and Sack 2003).

The central result of the paper is that the neuro-fuzzy model mimics almost perfectly the behaviour of the federal funds rate in the last 16 years. Moreover, the inclusion in the input data set of an indicator of the stock market allows a significant improvement in the prediction of the federal funds rate.

The paper is organized as follows. In section 2 we briefly present the Sugeno fuzzy model adopted in this paper. Section 3 is devoted to the presentation of the simulation conducted for the period 1987-2002. In section 4 we confront the results obtained with the neuro-fuzzy approach with other conclusions drawn by adopting alternative views on the working of monetary policy. Section 5 concludes.

2. The model

In this paper we propose an analysis of the behaviour of the central bank based on neuro-fuzzy techniques. We concentrate on the US for the period 1987-2002 and use this approach to build an adaptive model, pointing out the role played by the evolution of the monetary policy decision mechanism.

Generally speaking, each individual entity follows its own internal reasoning paths in order to process the pieces of information coming from the external world. Moreover, not only do individuals use strictly subjective approaches to the world, but they also continuously modify their reasoning paths by information from the external environment.

Similarly, we consider the decision process of the Federal Reserve as if it were driven by the choice behaviour of an individual entity. For, any central bank can be viewed as a single 'brain' system that receives a collection of input variables describing the state of the economy.

Let us assume an adaptive behaviour. From this point of view, not only do the number and the type of the collected variables change, also decision criteria are adaptive through time. Moreover, also as an individual entity, the present decisions of the Federal Reserve are influenced by the historical memory of past output reactions (with respect to the input set considered). Thus, the evolving criterion adopted is closely influenced by memory of past decisions.

It is worth noticing that this kind of memorization is not a passive data storing but an active updating process. For, besides collecting data, the Fed uses the criteria available at a certain time in order to combine information about past reactions with updated data. Finally, a value of the monetary policy instrument is established.

2.1. *Input and output data*

Let us consider T examples of K-dimension data input vector, $\underline{v}_t = (v_{t1}, ..., v_{tK})$, with $t = 1, ..., T$, and the same number of target responses, z_t. In particular, we have monthly observations, starting from January 1970. The input data vector represents the set of variables monitored by the Federal Reserve. In this paper we consider as inputs: the Industrial Production Index, the Consumer Price Index, the Unemployment Rate and the S&P 500 Monthly Dividend Reinvestment,[2] hence $K = 4$. The output, z_t, is the monetary policy instrument, namely the Federal Funds Rate. Thus, the starting data set is: $\{(\underline{v}_t, z_t)\}_{t=1}^{T}$.

First, we consider the log difference for the variables that are not expressed in terms of rates, then we take the average value of each variable over the last six months. Thus, we obtain $T - 6$ examples of input data vector, $\underline{x}_t$, and the same number of target responses of

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[2] The series are taken from FRED (Federal Reserve Economic Data) at the St. Louis Web site.

neural network given by z_t. These data represent the *training set* used: $\{(\underline{x}_t, z_t)\}_{t-6}^{T}$.

Hence, we consider the usual set of real and nominal variables which many believe to be under monitoring by central banks. However, we also include an indicator of the stock market. In doing so, we take seriously the repeated testimonies by Alan Greenspan in which the Federal Reserve Chairman has expressed his concern about equity prices. In particular, Greenspan has emphasized in recent years the role played by movements in the stock market in determining wealth effects capable of influencing aggregate consumption. Rigobon and Sack (2003) draw attention to another channel through which the stock market has affected the economic system in recent years provided by the influence on the cost of financing to businesses.

2.2. *ANFIS architecture and Sugeno fuzzy model*

This paper deals with an ANFIS[3] architecture. Lately, the fusion of Artificial Neural Networks (ANNs) and Fuzzy Inference Systems (FISs) has generated growing interest among researchers in different scientific areas. ANNs represent very efficient platforms for the implementation of non-linear associations. In many cases, neural networks reduce the difficulties of modeling and analysis of complex systems. On the other hand, FIS are suitable for incorporating the qualitative aspects of human experience within its mapping laws. In this sense, the rules of FIS provide a way to capture knowledge that is inherently affected by imprecision.

The fusion of ANNs and FISs into ANFIS offers the advantage of dynamical construction of input and output membership functions based on the nature of the data. ANFIS hybrid algorithm combines backpropagation gradient descent and least squares to create a fuzzy inference system, whose membership functions are interactively adjusted according to a given set of input and output data. This type of method improves the process of determining membership functions by both a very fast convergence due to hybrid learning and the ability to construct reasonably good input membership functions. Another interesting feature of ANFIS is that it provides more choices over

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[3] Adaptive Network-based Fuzzy Inference System. See, e.g. Jang (1993).

membership functions. The fuzzy model, at time t, can be formulated with R_t, a set of *if-then* rules:

$$R = \left\{ R_t^{(i)} \right\}_{i=1}^{I} = \left\{ \textbf{IF} \mathop{\textbf{and}}_{k=1}^{K} x_{tk} \text{ is } A_k^{(i)} \textbf{ THEN } y_t = f_i(\underline{x}_t) \right\}_{i=1}^{I} \quad (1)$$

where $A_k^{(i)}$ denotes linguistic terms in antecedent and $y_t = f_i(\underline{x}_t)$ is a crisp function corresponding to the output of the fuzzy model. The neurons composing the neural network architecture are organized in layers.

Layer 1: The output of the i-th node of this layer[4] is:

$$OL1_{tk}^{(i)} = \mu_{A_k^{(i)}}(x_{tk}) \quad (2)$$

Layer 2: Nodes of this layer multiply the incoming signals and send the product out. Each node output represents the firing strength $w_t^{(i)}$ of the corresponding rule. In general any T-norm operator will perform the fuzzy *AND* operator in this layer.

Layer 3: The output of the nodes in this layer are normalized firing strengths $\overline{w}_t^{(i)}$. The node function calculates the ratio of the i-th rule firing strength to the sum of rule firing strengths:

$$OL3_t^{(i)} = \overline{w}_t^{(i)} = \frac{w_t^{(i)}}{\sum\limits_{i=1}^{I} w_t^{(i)}} \quad (3)$$

Layer 4: The output of the i-th node of this layer is:

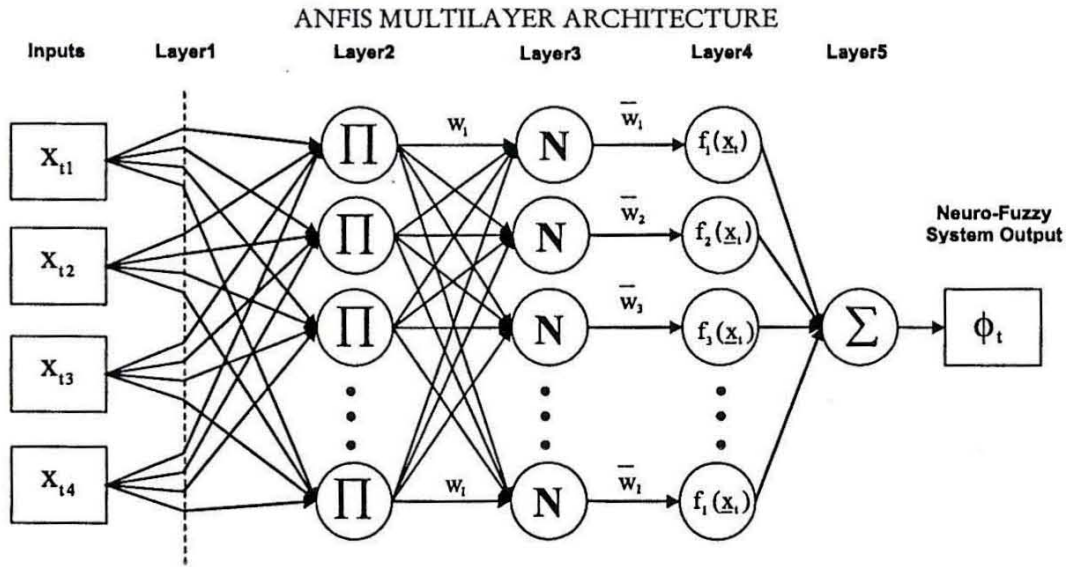$$OL4_t^{(i)} = \overline{w}_t^{(i)} f_i(\underline{x}_t) \quad (4)$$

Layer 5: The single node in this layer computes the overall system output as the summation of all incoming signals.

$$\phi_t = OL5_t = \sum_{i=1}^{I} \overline{w}_i f_i(\underline{x}_t) \quad (5)$$

A graphic representation is given in figure 1.

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[4] As membership function we use a generalized bell-shaped function.

FIGURE 1

ANFIS MULTILAYER ARCHITECTURE

2.3. *Data clustering and hybrid learning method*

Given separate sets of input and output data, we generate a fuzzy inference system by using fuzzy subtractive clustering.[5] The subtractive clustering method allows us to extract an initial set of rules that models the data features.

First, given that each point $\underline{x}_t$ could be a possible cluster center, we use the density measure at data vector $\underline{x}_t$ defined as:

$$D_t = \sum_{j=1}^{T} \exp\left(-\frac{\|\underline{x}_t - \underline{x}_j\|^2}{(r/2)^2}\right) \tag{6}$$

where r is a positive constant. Notice that, if the value of density is high for a data vector, it means that it has several neighbouring data vectors. In particular the radius r defines a neighbourhood.

After calculating the density measure of each data point, the one with the highest density measure is elected as the first of the cluster center. Let $\underline{x}_{c1}$ be the vector selected and D_{c1} its density measure. The density measure of each data vector is revised by:

$$D_t = D_t - D_{c_1} \exp\left(-\frac{\|\underline{x}_t - \underline{x}_j\|^2}{(r'/2)^2}\right) \tag{7}$$

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[5] Proposed by Chiu (1994).

where r' is a positive constant. After revising the density measure for each data vector, the next cluster center $\underline{x}_{c2}$ is selected and all of the density measures for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated. These cluster centers are reasonably used as the centers of the fuzzy rules' premise in a Sugeno fuzzy model.

If a reliable set of input-output data is available from the training dataset, and an initial set of rules that models the data behaviour is extracted, then it is possible to generate the adaptive learning on measured data. Notice that we assume that we have the desired target output of network for inputs for training data set.

We use a two-pass learning cycle that consists of both forward and backward steps. In the forward pass of the hybrid algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent. If we denote an input-output relation as a parametrized function $\varphi = F(\underline{x}_t, S)$, where F denotes the overall function of the adaptive network, φ_t is the output value and S represents the set of parameters to optimize.

If there exists a function H such that the composite function $H \circ F$ is linear in some elements of S, then these elements can be identified by the Least Square method. If the parameter set is divided into two sets, $S1$ and $S2$, it is defined as:

$$S = S1 \oplus S2 \tag{8}$$

where $\oplus$ denotes direct sum, with $S = \{S1 \cup S2\}$, and $\{S1 \cap S2 = \varnothing\}$, such that $H \circ F$ is linear in the elements of $S2$, the function H can be represented as:

$$H(\phi) = H \circ F (\underline{x}_t, S) \tag{9}$$

For given values of $S1$, using T training data, we can represent the above equation into the matrix equation $\mathbf{B} = \mathbf{AX}$, where $\mathbf{X}$ contains the elements of $S2$.

If $|S2| = \mathbf{M}$, where M represents the number of linear parameters, then the dimension of matrix $\mathbf{B}$, $\mathbf{X}$ and $\mathbf{A}$ are $T \times 1$, $M \times 1$ and $T \times M$, respectively. This is solved by:

$$\mathbf{X}^* = (\mathbf{A}^{-1}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{B} \tag{10}$$

where $(A^{-1}A)^{-1}A^{T}$ is the pseudo-inverse of A, if $A^{-1}A$ is non-singular. The LSE minimizes the error $\|AX - B\|^2$ by approximating X with X*.

Let the t-th row vector of matrix A be a_t^T and the t-th element of B be b_t^T. Then for $t = 0, 1, ..., T-1$ we can calculate:

$$X_{t+1} = X_t + P_{t+1} a_{t+1}(y_t^T - y_{t+1}^T + b_{t+1}^T P_t)$$

$$P_{t+1} = P_t - \frac{P_t a_t + b_{t+1}^T P_t}{1 + a_{t+1}^T P_t a_{t+1}} \tag{11}$$

The LSE X* is equal to X_T. The initial condition of the system are $X_0 = 0$ and $P_0 = m \cdot I$, where m is a positive large number and I denotes the identity matrix of dimension $M \times M$.

Secondly, in the backward pass, the error signals, the derivatives of the error measure with respect to each node output, propagate from the output end toward the input end. The error measure E_t, for the t-th entry ($1 \leq t \leq T$) of the training data, is:

$$E_t = \sum_{i=1}^{N(L)} (d_i - O_{L,i})^2 \tag{12}$$

where $N(L)$ is the number of nodes in layer L, d_i is the i-th component of *desired* output vector and $O_{L,i}$ is the i-th component of actual output vector produced by presenting the t-th input vector to the network. We want to minimize the overall error measure $E = \Sigma_{t-1}^T E_t$ At the end of the backward pass for all training data the parameters in S1 are updated by the steepest descent method. For the simple steepest descent method the update formula for the generic parameter α is:

$$\Delta\alpha_i = -\eta \frac{\partial^+ E}{\partial\alpha} \tag{13}$$

in which $\eta = \kappa/\sqrt{\sum_\alpha(\partial E/\partial\alpha)^2}$ denotes the learning rate, where κ is the step size, and $\partial^+ E/\partial\alpha$ is the ordered derivative.

2.4. *Forecasting FED behaviour*

At any time t, a neuro-fuzzy architecture is produced from the training data set (x_i, z_i), $i = 1, ..., t$, by the learning algorithm. Thus, we obtain a neuro-fuzzy system which has been trained by using data

until the considered time.[6] Such a system can be represented simply as a parametrized function of the variables monitored by the Fed that changes over time,[7] namely $F_t(.)$.

The central bank makes use of its brain system trained until time t to decide a possible value for the monetary policy instrument with respect to the key variables at time $t + 1$. Furthermore, we suppose that the central bank weights its decision by the past value of the monetary policy instrument. Thus, the final output is obtained by taking into account the tie represented by the value of the instrument ϕ_t that the Fed fixes at the previous period of time:

$$\phi_{t+1} = (1 - \lambda)F_t(\underline{x}_{t+1}) + \lambda\phi_t \qquad (14)$$

where λ denotes the weight of the monetary policy instrument at time t with respect to fuzzy model output at time $t + 1$.

3. The simulation conducted for the period 1987-2002

In this section we present a simulation of the Federal Reserve's behaviour for the period from 1987 to 2002.

In our experiment we assumed that λ keeps constant for all the considered period. In particular, we fixed its value at $\lambda = 0.6$ which, in

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[6] Hadjili and Wertz (2002) have recently criticized the Takagi-Sugeno fuzzy model. The authors observe that this approach implies the identification of all the parameters of the model and, as a consequence, requires a large computation time. Thus, they propose a systematic procedure aimed at estimating the optimal number of fuzzy rules and at selecting the relevant input variables as antecedents. Undoubtedly, the contribution of Hadjili and Wertz outline an important shortcoming associated to the Takagi-Sugeno fuzzy model. Yet, it is worth noting that the main results presented in this paper, which concern the evolution of the federal funds rate and the behaviour of the Federal Reserve, are not influenced by this potential flaw of the model.

[7] In a recent paper Angelov and Filev (2004) develop an approach to structure and parameter identification of Takagi-Sugeno fuzzy modeling which is based on recursive updates of model structure and parameters. An important feature of this evolving Tagaki-Sugeno model concerns the possibility to update the structure when new data become available. Moreover, this method does not require that all the data is available at the start of the process of learning. Hence, this new evolving model seems to be another good candidate for investigating the adaptive behaviour of the Federal Reserve. In future extensions of this research on central banks' behaviour in the conduct of monetary policy, we want to explore the potential advantages given by this new approach. We thank an anonymous referee for drawing our attention on this reference.

our view, represents a reasonable choice expressing the Federal Reserve path dependence with respect to past values of the monetary policy instrument. Indeed, it is well known that central banks usually modify the interest rate smoothly, thus avoiding abrupt changes in the conduct of monetary policy.[8]

The simulation proceeds as follows.

1. At any given time, beginning from 1987, we produce a new neuro-fuzzy system from the pieces of information given by the training set at time t. Remember that the training set at time t is composed of both $\underline{x}_t$ (decision relevant variables) and z_t (federal funds rate target responses).

2. Using values of $\underline{x}_{t+1}$ in the system obtained allows us to generate the estimated value of the funds rate for the period $t + 1$.

3. We obtain a time series of the estimated values of the federal funds rate from 1987 to 2002 by repeating the steps above sequentially with respect to time and thus producing a neuro-fuzzy system for each month within the period of time considered. In other words we produce a number of systems equal to the number of estimates we generate.

4. We compare graphically the series of actual funds rate z_t with the series of simulated values ϕ_t obtained from the steps above.

In our latest experiments, we have introduced an indicator of the stock market. Let us point out that introducing such a variable has been fundamental in order to improve the experimental results. Figure 2 shows the similarity of the federal funds rate dynamics with respect to our prediction.

Note that the model is able to capture not only the sign of the change in the target variable with respect to time, but also its percent-

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[8] It is worth noticing that our choice of an interest rate smoothing, or inertia parameter λ of 0.6 plays an important role across the whole simulation process. Indeed, the particular value selected is consistent with other results obtained in the field of research devoted to estimation of monetary policy rules (see e.g. Clarida, Galí and Gertler 1998). Moreover, it seems also consistent with the conduct of monetary policy in the United States in the Greenspan era. Nevertheless, we want to stress that the introduction of a fixed parameter is not completely consistent with the neuro-fuzzy framework and thus, at this stage of the research, it represents a potential weakness of the approach utilized in this paper. We aim to develop, in our future research on the behaviour of central banks, a framework which allows the smoothing parameter to be endogenized.

age level. In fact, notice that the tracking error, Tr, simply defined as the difference between the two series, is $|Tr| \leq 1.1$ for each considered time.

Even though our approach does not require any explicit assumption on the error distribution, we perform a simple statistical analysis in order to check the quality of our results. First, we compare graphically the tracking error values with the normal distribution. The quantile-quantile plot figure 3 shows strong similarity between the empirical distribution of the tracking error and the normal distribution.

FIGURE 2

ACTUAL AND SIMULATED FEDERAL FUNDS RATES
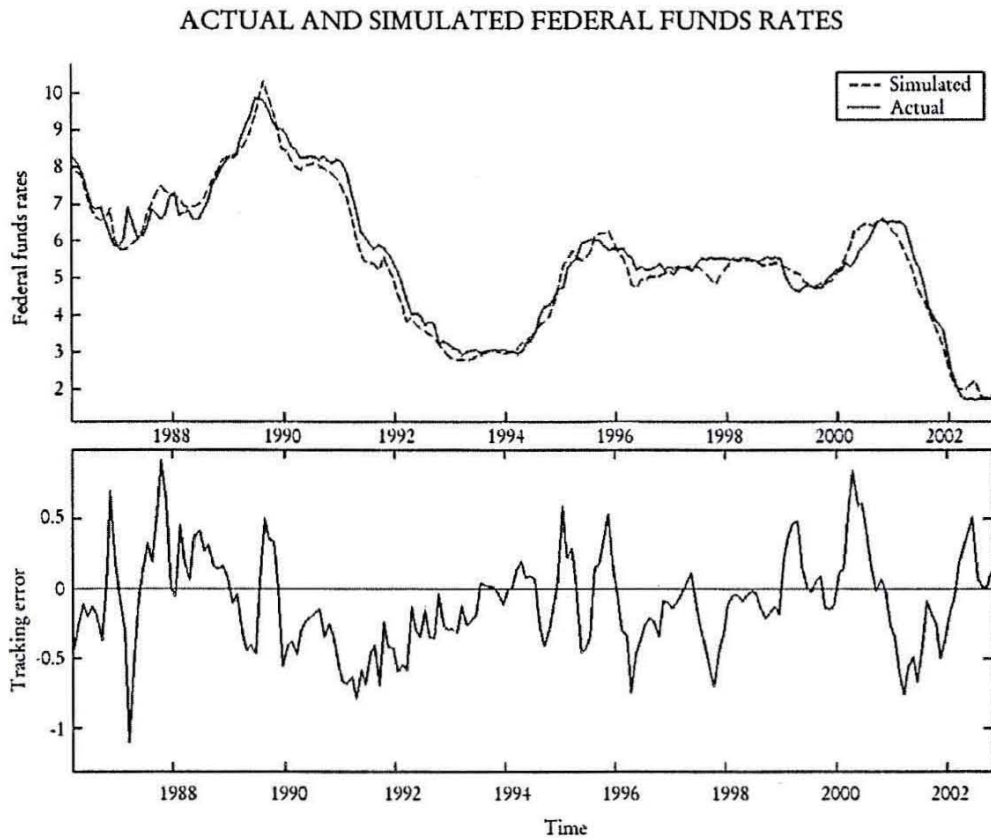
The results from the graphical comparison are confirmed by Shapiro-Wilk normality test. The p-value = 0.823 does not show evidence against the null hypothesis of normality of the tracking error. Therefore, in this case, it is reasonable to conclude that the tracking error follows the typical behaviour of a random measurement error.

Under this perspective, a simple MLE estimate of the mean $(\hat{\mu}_{Tr})$ and standard error $(\hat{\sigma}_{Tr})$ allows us to obtain a confidence interval for the tracking error.

$\hat{\mu}_{Tr}$	$\hat{\sigma}_{Tr}$	95% C.I. for the tracking error
−0.0533	0.3488	(−0.7509, 0.6443)

The estimate of the mean close to zero and a quite narrow 95% confidence interval strengthen our conclusion that the simulated series of the Fed interest rate mimics closely the actual behaviour of the monetary policy instrument.

Thus, the experimental results show the capability of our model to explain quite precisely the behaviour of the federal funds rate. We do not detect, for most of the periods, a particular tendency for the simulated series to lead or lag the nominal interest rate. Nevertheless, it is worth noticing the ability of the estimated values to anticipate, at the beginning of 2000, the impending change in the conduct of monetary policy which in the subsequent months will have been dictated by the slowdown of the economy. A possible explanation of this result is

FIGURE 3

TRACKING ERROR ANALYSIS
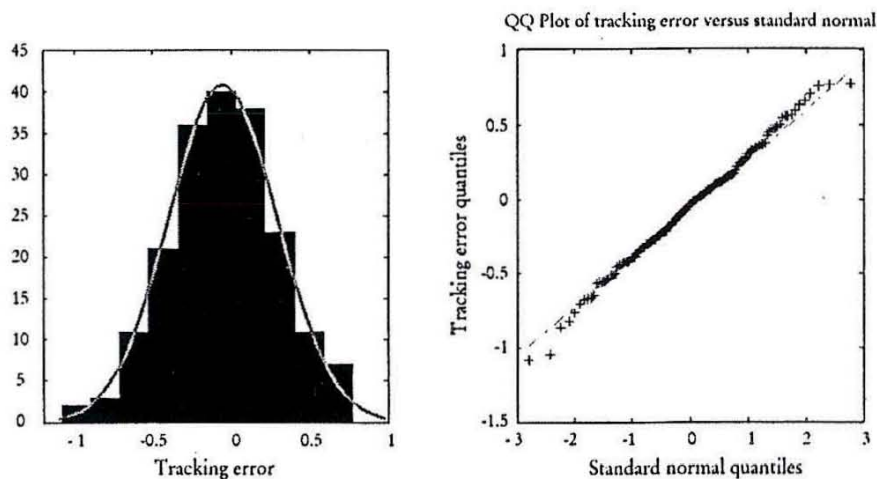
that the stock market acted correctly, at least in this phase, as a leading indicator, reaching its peak at March 2000, whereas real macroeconomic data showing the first clear indications of the economic slowdown appeared only about six months later. Of course, given the importance that the Federal Reserve attributes to movements in the stock market, the collapse which followed the period of 'irrational exuberance' exerted an important influence on the conduct of monetary policy, reinforcing the bias of the central bank towards the loosening of monetary conditions.[9]

4. A comparison with the results obtained by adopting alternative approaches

The impressive result shown in the previous section is that a simple ANFIS architecture combined with a Sugeno fuzzy model is able closely to reproduce the path followed by the federal funds rate in the last 16 years.

The aim of this section is briefly to compare the approach and the results obtained in the present paper with other leading lines of research concerning the analysis of monetary policy.

We have emphasized that the two pre-eminent approaches in recent decades were, respectively, i) structural VAR models aiming to trace back the dynamic effects of monetary policy shock on a selected set of macroeconomic variables and ii) estimation, by using traditional econometric techniques, of the central bank's reaction function.

Let us then assume that the Federal Reserve adopts the federal funds rate as its monetary policy instrument. Systematic policy can be expressed by:

$$\phi_t = F\left(\Omega_t\right) + \varepsilon_t \tag{15}$$

where Ω_t represents the information set of the policy makers. Hence, $F\left(\Omega_t\right)$ provides the systematic component of monetary policy whereas

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[9] We wish to emphasize that introducing an indicator of the stock market revealed itself of paramount importance in enabling an improvement of the experimental results. We also conducted a simulation (not reported here) without including the stock market and found a relevant deterioration in the prediction of the federal funds rate.

ε_t represents the unexpected component, i.e. the monetary policy shock.

In the VAR literature Ω_t usually contains a set of variables which can be ideally separated into target variables, e.g. unemployment and inflation and other macroeconomic series that are useful for predicting the future behaviour of some key variables, e.g. the commodity price index. In order to study the dynamic effects on inflation and unemployment of a monetary policy shock, a set of identifying restrictions needs to be imposed. For example, in Christiano, Eichenbaum and Evans (1999) a causal (recursive) structure is assumed on the basis of informational assumptions regarding the conduct of policy.

Undoubtedly, both the approaches gave important insights into the working of monetary policy and its effects, at different frequencies, on the economic system. Nevertheless, they have been subject to some criticism. As far as the structural VAR approach is concerned, perhaps the most important shortcoming derives from the conclusion, common to many empirical investigations and robust to different strategies of identifying restrictions, that only a small part of output variance can be ascribed to monetary policy shocks and that a dominant role is instead played by the systematic component of monetary policy. In other words, the surprise component of monetary policy is likely to represent only a secondary channel through which the central bank influences the economic system.[10]

Such shortcomings have led a number of researchers (see, e.g. Clarida, Galí and Gertler 1998) to concentrate on the systematic component of monetary policy. As for the estimation of central bank's reaction functions, a good deal of uncertainty is related to the selection of a set of unobservable economic variables, the most important being the output gap. Moreover, a recent strand of research has drawn attention to the possibility of systematic errors in assessments regarding the outlook of the economy in real time and hence, as a consequence, also the implementation of simple rules turns out to be complex in practice (see, e.g., Orphanides 2001).

As far as the question of estimating unobservable macroeconomic variables is concerned, it is worth pointing out that the approach of this paper does not face this kind of problems. The reason is that in

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[10] A recent and comprehensive survey is provided by Christiano, Eichenbaum and Evans (1999).

the context of fuzzy logic a precise indicator of the macroeconomic conditions, such as the natural level of output, has little sense since, within this approach, it is never completely true or false that the economic system is experiencing a phase of high or slow growth: this characterization of the economic situation obtains only a certain degree of membership, and such memberships are not sharply separated.

Nevertheless, we believe that the most important question arising from the recent research on modeling the central bank's reaction functions attains the fixed coefficients response which it imposes on the Fed's behaviour. It is unbelievable that the central bank, over a period of 16 years, always reacted in the same way and with the same magnitude to discrepancies between target and observed values of macroeconomic variables.

In this paper we have repeatedly emphasized the advantage of an evolutive approach to monetary policy since it affords the central bank the possibility to learn from its experience and, moreover, it defines the operation assumptions in the form of flexible rules, thus providing a more adequate characterization of the behaviour of the central bank.

5. Conclusions

The simulation conducted in this paper has shown that the neuro-fuzzy approach to the behaviour of the central bank represents an interesting alternative to the characterization of US monetary policy based on the estimation of structural equations, since it allows a good description of the behaviour of the monetary policy instrument, i.e. the federal funds rate.

Following the seminal work of Taylor (1993), structural equation models usually analyze the systematic response of the nominal interest rate to the contemporaneous (and possibly lagged) values of inflation and the output gap. Indeed, it is easily recognized that central banks monitor a wider set of variables, including indicators of the stock market. Thus, in the present paper we found that inclusion in the input data set of an indicator of the state of confidence of the stock market turned out to be very important in shaping the behaviour of

the federal funds rate in recent years. Note that an extension of the input data set is also possible in the context of the estimation of monetary policy rules. However, serious problems of simultaneity are likely to arise.

In our view, another important shortcoming of the traditional econometric techniques (included the structural VAR approach) applied to monetary policy is that they predict a fixed response of nominal interest rates in the presence of discrepancies between target and observed values of macroeconomic variables. For example, in the Greenspan era, the estimated consensus coefficient regarding the response of the Federal Reserve to current inflation is slightly above one. The implication is that throughout the 16 years of Greenspan's headship in all the cases in which a proxy of the future inflation was 1% above the target, there has been an increase in the federal funds rate of slightly more than 1%. Clearly, this imposes a strait jacket on the conduct of monetary policy since it does not allow for flexibility and, not less important, prevents the possibility for the Fed to develop a process of learning about the working of the economic system. The neuro-fuzzy approach avoids this rigidity since: *i*) it allows the Fed the possibility to learn from its experience; *ii*) the Fed is faced with a complex system and, as a consequence, the operation assumptions need to be set in form of vague (flexible) rules. Ambiguous concepts like normal unemployment or low inflation depend upon the historical and economic context: in the 1990s the notion of normal unemployment (and low inflation) was very different as compared to one or two decades before. Indeed, the adoption of vague rules is the essence of fuzzy systems whereas flexibility is a feature of artificial neural networks.

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