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Forecasting Exchange-Rates via Local Approximation Methods and Neural Networks

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Abstract

There has been an increased number of papers in the literature in recent years, applying several methods and techniques for exchange - rate prediction. This paper focuses on the Greek drachma using daily observations of the drachma rates against four major currencies, namely the U.S. Dollar (USD), the Deutsche Mark (DM), the French Franc (FF) and the British Pound (GBP) for a period of 11 years, aiming at forecasting their short-term course by applying local approximation methods based on both chaotic analysis and neural networks.

1. Introduction

Predictability issues with special reference to stock and foreign-exchange markets seem to attract increasing interest during the last few years. Concentration on forecasting developments related to exchange rates, in particular, is not only justified by the risk-versus-return tradeoff, but, in addition, by the fact that the exchange rate is often used as policy instrument for tackling macroeconomic targets, like price stability or balance-of-payments equilibrium. But even in cases in which the exchange-rate is allowed to fluctuate in the international markets within margins that vary considerably depending on the case, the fact remains that the various central banks retain the power to intervene both in the domestic and international markets, manipulating the exchange-rate of their respective currencies whenever the need arises. Such interventions are usually of drastic nature, taking place either by foreign-exchange-reserves manipulation or by resorting to interest rate policy, thus increasing the noise level which characterizes the behavior of the time series involved. This issue introduces a considerable degree of difficulty when it comes to forecasting, although, as Taylor (1995) points out, empirical evidence on the link between official intervention and exchange-rate expectations is rather unclear.

The fact remains, however, that the relevant literature is full of cases in which forecasting the exchange-rate of various currencies yields results which are either poor (Marsh and Power, 1996; Pollock and Wilkie, 1996; West and Cho, 1995), or difficult to interpret (Kim and Mo, 1995; Lewis, 1989). Some authors even conclude that there is no such thing as best forecasting technique and the method chosen must depend on the time horizon selected or the objectives of the policy-maker (Verrier, 1989). There are, in addition, cases in which high persistence but no long range cycles have been reported (Peters, 1994), something that leads to the conclusion that currencies are true Hurst processes with infinite memory. On the other hand, long term dependence, supporting that cycles do exist in exchange rates, has been found by other researchers (Booth et. al., 1982, Cheung, 1993; Karytinios at. al., 1999). Despite various attempts to settle such controversies (Pesaran and Potter, 1992), it is still not clear whether the source of the dispute is, the differences with respect to sample size, noise level, pre-filtering processes etc. of the various data sets employed, or the variety of tests that have been used, or even a combination of these factors.

But the major problem associated with exchange-rate predictability has been indicated by Meese and Rogoff (1983) and refers to the failure of the structural models to outforecast the random walk model, due, among other things, to difficulties in modeling expectations of the explanatory variables. The matter has attracted increasing attention in the literature since then by authors like Leventakis (1987), De Grauwe et. al. (1993), Frankel (1993), Baxter (1994) and Pilbeam (1995). Although all sources agree on the empirical failure of models to forecast exchange-rate movements, none of them is able to provide a satisfactory explanation concerning the reasons why this is so. Most of

them, however, seem to agree on the possibility that expectations are much more complicated than what modern exchange-rate theories have specified (see e.g. Pilbeam, 1995), primarily because the rapid flow of information as well as the shift in the demand and supply pattern bring about significant influence on the market movements (Mehta, 1995). Thus several authors seem to conclude that even the forward rate, which is considered very efficient when used to improve forecasting performance, can sometimes fail in contributing towards this direction (e.g. Levich, 1989).

Turning to the case of the Greek drachma, attempts to forecast its exchange rates versus major currencies are rather scarce. Karfakis (1991) has concentrated on the drachma/USD exchange rate, while Koutmos and Theodosiou (1994) and Diamandides and Kouretas (1996), have explored the predictability of the drachma rates with respect to a number of European currencies, the USD and the Japanese yen. In all these cases, however, the analysis is conducted in the context of exchange-rate models, with all the drawbacks that such a choice might entail.

In face of the limited success of empirical literature to interpret exchange-rate movements researchers have resorted, quoting Taylor (1995), to the use of “recently developed sophisticated time-series techniques”. Indeed, one such technique is that which relies on tracing chaotic behavior in the exchange-rates series examined, as well as that of artificial neural networks. These, being data-driven approaches, have been considered preferable to traditional, model-driven approaches used for forecasting purposes, on the grounds of our earlier evaluation in the context of the literature cited. In fact, exchange-rate literature has been recently enriched by an increasing number of studies which resort to using neural network algorithms which lead to better results

concerning exchange-rate forecasting compared to “conventional methods” (e.g. Mehta, 1995; Steurer, 1995; Refenes and Zaidi, 1995).

This paper uses both chaos theory and neural networks to predict the exchange rate of four major currencies against the Greek Drachma, namely the U.S. Dollar (USD), the Deutsche Mark (DM), the French Franc (FF) and the British Pound (GBP). Our primary goal is to investigate the extent to which the time series involved exhibit chaotic behavior, a prerequisite for applying the well known Farmer’s algorithm for prediction. The results obtained on the basis of the application of Farmer’s algorithm will, at a second round, be compared to the predictions obtained using another approach, namely the emerging technology of artificial neural networks. Taking into account that so far the results of research in this area have not established a general structural character of currency markets, this analysis is expected to be useful for comparison purposes as well. The results of both techniques are then compared focusing on the best prediction performance.

1.1 Methodology and Data

Our time series consist of daily exchange rates of the four currencies already mentioned against the Greek drachma. The rates are those determined during the daily “fixing” sessions in the Bank of Greece. The data cover an 11-year period, from the 1st of January 1985 to the 31st of December 1995, consisting of 2660 daily observations, a population which is considered relatively small compared to that used in similar cases in the natural sciences, but large enough compared to other studies in Economics and Finance, in several of which the number of observations barely reaches 2000. The sample series have been transformed to the first differences of their natural logarithms

in order to remove the trend. During the neural networks implementation, we used the logarithmic data, so that results are directly comparable to those obtained using Farmer's algorithm. We also tested the predicting ability of neural networks when incorporating the actual spot rates, since this option offers the advantage of not being affected by the presence of trends or discontinuities in the series involved. Mehta (1995), however, suggests avoidance of using the actual spot rates both because of the non-stationary and quite random nature of this series and because of the daily infinitesimal changes involved, something which reduces the learning ability of neural networks. Taking these suggestions into account we have tackled this last problem by rescaling our series in the range $[0,1]$ in order to use the sigmoid activation function. Our experiments showed that non-stationarity or randomness that can be observed mainly by visual inspection did not affect learning and that forecasting results obtained were highly satisfactory.

A final remark concerns the high jumps observed in the first 2 years (1985 and 1986) of the series, immediately affected by the drachma devaluation. These samples were excluded from the data library used in both Farmer and neural networks experiments, characterized as outliers that correspond to significant level of noise. Other such spikes observed scattered through the data series (e.g. 1992, 1993, 1995) were not removed because they are low intensity and duration periods. Extensive simulations with both methods showed that the course of forecasting was not affected by their presence.

The structure of this paper is as follows: Section 2 describes the leading role of the exchange-rate policy in the context of an overview of the macroeconomic policies followed during the last two decades. Section 3 includes a statistical and a non-linear

analysis of the logarithmic data. Section 4 describes the methods and results of local approximation forecasting on our data. The application of neural networks takes place in section 5, while section 6 is devoted to a discussion on the economic interpretation of the results. Finally, our conclusions are presented in section 7.

2. The Greek Environment

The exchange rate has been used as a major policy instrument in Greece since March 1975, when the drachma ceased to be pegged to the US dollar in terms of a fixed exchange rate. The reasoning behind the extensive use of exchange-rate policy by the authorities was based on its effectiveness thanks to its speed, flexibility and politically costless action. This policy aimed at guaranteeing an acceptable level of price competitiveness of Greek goods and services in the international markets and reducing the balance of payments deficit. Since 1975 and until the early 90's, however, the drachma had been following a depreciating trend which, in parallel to the implementation of an expansive monetary policy, has contributed to preserving high inflation rates (Bank of Greece, 1984, p.31). In fact, for the time period under review, this policy has provided for a devaluation in 1985 which resulted to the drachma depreciating by 16.3% in 1985, and 23.1% in 1986. This is shown by sharp peaks in Figures 1(b), 2(b), 3(b) and 4(b), which, it is reminded, indicate the devaluation by just a daily sharp peak, since the figures used are percentage changes of exchange rates rather than the currency rates themselves. The beginning of the 90's, however, introduces a dramatic policy change with the authorities realizing the extent of the failure of this accommodating exchange rate policy (Bank of Greece, 1986; Brissimis and Leventakis, 1989; Karadeloglou et. al., 1998; Zombanakis, 1997). More specifically, this policy option proved to be rather unfortunate, since high production costs resulted to a considerable erosion of the degree of

competitiveness of the Greek products in the international markets. The underlying increased import penetration of the Greek economy due to the inability to resort to structural changes in its production structure, is a supply-side problem, touching upon issues like the application of the Marshall-Lerner condition and the existence of an inverse J-curve effect characterizing the Greek economy (Karadeloglou, 1990). Thus, the exchange rate policy during the mid-90's changes to becoming "the hard - drachma policy", in the sense that the rate of depreciation does not fully accommodate the inflationary gap between Greece and its trading partners. Additional intervention measures have also been imposed in order to improve productivity, curtail production costs, adjust the supply side to changes in demand, and face the impact of seasonal or irregular factors on the drachma exchange rate. Concerning the drachma rates, the depreciation versus the ECU declined to 4.1% for 1995 and 0.6% in 1996, acting as an anti-inflationary policy instrument (Karadeloglou et. al., 1998) in anticipation of the drachma participation with the ERM (Bank of Greece, 1995). This policy has proven to be more than successful since, its drastic anti-inflationary impact was accompanied by a significant interest-rate reduction representing a relief for the budget deficit and a decrease of the capital cost of the business sector. Thanks, also, to the "hard-drachma", increases in servicing the foreign-currency denominated public debt have been avoided, the foreign-exchange risk has been restricted, while the cost of the imported raw materials for Greek export firms, the products of most of which bear a high import component, has been held constant. Finally, the anti - inflationary effect of the "hard - drachma" policy has added to the effort of attaining the price - stability target, a requirement for the country's EMU membership (Bank of Greece, 1994, 1997).¹

¹ The recent change in the exchange-rate policy culminating with the drachma devaluation seems to contradict this reasoning. This is a very interesting issue, which however is beyond the scope and the time profile of the present paper.

As this policy undoubtedly provided for increased degree of discipline for the drachma fluctuations versus the ECU participant currencies, it is natural to expect that the predictability of the drachma/USD rate is reduced compared to that of the drachma rates vis-à-vis the rest three currencies, due to the absence of any sort of relationship or correspondence in terms of policy targeting between the drachma and the USD.

3. Statistical and Non-Linear Analysis

3.1 Statistical Description of the Data

The basic statistical properties and the logarithmic time series plots of the four data series involved are listed in Table 1 and Figures 1(b), 2(b), 3(b) and 4(b). All series have been characterized by strong skewness and kurtosis, while three out of four have indicated absence of any significant autocorrelation, with the exception of the DM/GRD, which has displayed first order autocorrelation and for which an AR(1) specification has been employed. In general the statistical properties of all series are rather similar in terms of distributional features something which is, to a large extent, explained by the significance which the authorities have attributed to the drachma exchange-rate versus major currencies as a policy instrument during the period under consideration. It must be borne in mind that the data depicted in the graphs are first differences of the logarithms of the original data, which makes it, in fact, percentage changes. The interpretation of these diagrams, therefore, requires particular attention. In Figures 1(b), 2(b), 3(b) and 4(b), for example, a devaluation will appear as a sharp peak corresponding to just one daily observation, with the subsequent daily data dropping again to pre-devaluation levels.

3.2 Correlation and Generalized Dimensions

A number of measures of complex time series have been developed based on concepts of non-linear dynamics. These include correlation dimension (Grassberger and Procaccia, 1983; Tsonis, 1992) of the time series from the analyzed system, aiming at distinguishing between chaoticity and randomness. The correlation dimension gives a statistical measure of the geometry for the reconstructed attractor. In deterministic chaotic systems the correlation dimension is frequently (but not always!) a fractional number and is independent of the embedding dimension m , when m is large enough (Schuster, 1988; Theiler, 1986). This work is not intended to provide for a complete chaotic analysis of the series under study. Instead, we employ the dimension test, the most popular among methods for revealing evidences of chaos, in order to use Farmer's algorithm, a technique which is proven to have very good results in predicting chaotic, noise-free signals.

The procedure to calculate the correlation dimension requires constructing time-delayed copies of the matrix:

$$a_k = [X(t_k), X(t_k + \hat{\delta}), X(t_k + 2\tau), \dots, X(t_k + (m-1)\tau)] \quad (1)$$

If the underlying state space of a system has d dimensions then the embedding space needs to have $2d+1$ dimensions to capture completely the dynamics of the system (Takens, 1981). In practice we compute the correlation dimension using various embedding dimensions m . The correlation dimension can be calculated from the correlation integral $C_m(r)$ given by

$$C_m(r) = \frac{2}{N^2 - N} \sum_{k,j=1}^N H(r - |a_k - a_j|) , a_k \neq a_j \quad (2)$$

where r is the radius of the located hyperspheres, $|a_k - a_j|$ is the Euclidean distance between the vectors a_k and a_j , N is the total number of elements of the signal and H is the Heaviside function. The Heaviside function is equal to 1 if $r \geq |a_k - a_j|$ and is equal to 0 if $r < |a_k - a_j|$. The correlation dimension $d(m)$ is expected to scale as a power of r , that is

$$C_m(r) \propto r^{d(m)}, r \rightarrow 0 \quad (3)$$

where $d(m)$, the correlation dimension of embedding dimension m , can be estimated by the slope of $\log(C_m(r))$ versus $\log(r)$, i.e.

$$d(m) \equiv \lim_{r \rightarrow 0} \frac{\partial \ln C_m(r)}{\partial \ln(r)} \quad (4)$$

We work as follows : the plot of the slope of $\partial \ln C_m(r) / \partial \ln(r)$ versus $\ln(r)$, for r values between 0.5 and 2, is constructed for each m . Correlation dimension d can then be estimated directly from the slope versus $\ln(r)$ (Bountis et. al., 1993).

We expect d to vary with m until m reaches the level of $2d+1$. Once this occurs, if the system under study is not a random one, d saturates to a value called d_{sat} and becomes independent of m . Thus, d_{sat} gives a fair estimate of the correlation dimension of our system. For a truly random system d will constantly increase according to m because the system will tend to fill all the available space for each m .

We calculated the correlation dimension for the four raw data series with the embedding dimension ranging from $m=2$ to $m=20$ and $\tau=1$ and the results were the following: DM and FF showed a saturating dimension of approximately 6 and 8 respectively, while USD and BP had their dimensions rising higher, at approximately 12 and 14 respectively, without showing any evidence of clear saturation (Figure 5). We also tested DM using $\tau=2$ (recalling the AR(1) correlation), but our results remained practically the same. This result tends to show that the behavior of the drachma rates versus the DM and FF is more disciplined, a fact which is absolutely justified by the ERM membership of these two currencies, as well as by the orientation of the Greek exchange-rate policy that uses the ECU as a guideline, in which the share of both currencies together amounts to more than 50% .

Pre-filtered with AR(1), the DM series did not show any significant change in the resulted dimension either. These results suggest that two of our series, DM and FF, can be explained by determinism, however, a simple low-dimensional attractor is highly unlikely. USD and GBP on the other hand seem to be more consistent with a random explanation. Their dimension keeps rising almost like m which is a strong symptom of a random behavior. Yet, we must be very cautious with the interpretation of these results because of the small length in data series, which can lead to either an upward bias in the case of chaotic data or to a downward bias in the case of random data (Ramsey and Yuan, 1989;1990). Thus, we cannot rule out the possibility of a deterministic part in USD and GBP signals, which may be perfectly covered by noise. We decided, therefore, to apply Farmer's algorithm to all four series, although only two of them (out of four series) favored a (more) clear chaotic behavior, aiming at tracing further indications regarding the diversification of the structure of our series. Direct comparison

of the predictive performance will then be feasible, confirming the deterministic or stochastic explanation given above.

4. Local Approximation Forecasting - Farmer's Algorithm

There has been a considerable number of papers in the literature, particularly during the recent past, applying the methods and techniques of non-linear dynamics to forecasting financial time series. Since the level of dimensionality (correlation dimension) provides evidence that at least two of the series exhibit chaotic behavior, while the rest two are either deterministic with a substantial amount of noise or just random, we use chaotic dynamics and more specifically, Farmer's algorithm, to predict the future course of our time series.

According to this algorithm (Farmer and Sidorowich, 1987) predictions are made using a local approximation approach as follows : first we embed our series in an m -dimensional space, where m is suggested to be at minimum greater or equal to the attractor's dimension d , and produce the x -vectors shown in equation (1). To predict $x(t+T)$ we find the k nearest neighbours of $x(t)$ that minimize the Euclidean metric $\| \cdot \|$, let these be $x(t')$. From this point on, we have a variety of ways to construct the local approximator. We can take $k=1$ (zero-order approximation) and $x_{\text{pred}}(t,T)=x(t'+T)$, or let k vary, usually starting with $k>m+1$ for better results and then fit linear or higher-order polynomials to the pairs $(x(t'),x(t'+T))$.

The accuracy of predictions is tested using the Normalized Root Mean Square Error (NRMSE):

$$\text{NRMSE}(n) = \frac{\text{RMSE}(n)}{\sigma_{\Delta}} = \frac{\text{RMSE}(n)}{\sqrt{\frac{1}{n} \sum_{i=1}^n [x_{\text{act}}(i) - \bar{x}_n]^2}} \quad (5)$$

where,

$$\text{RMSE}(n) = \sqrt{\frac{1}{n} \sum_{i=1}^n [x_{\text{pred}}(i) - x_{\text{act}}(i)]^2} \quad (6)$$

If NRMSE=0 then predictions are perfect; NRMSE=1 indicates that prediction is no better than taking x_{pred} equal to the x -mean. We also test prediction with the correlation coefficient r between the actual and predicted series.

As earlier stated, the application of Farmer's algorithm to all four series aims at distinguishing between the somewhat clear chaotic structure of the DM and FF series on one hand, and the ambiguous behavior of the USD and the GBP on another. In fact in the case in which the latter are truly random signals, then this method is expected to result to a poor predictive performance. We run our tests with a rolling library, $\tau=1$, embedding dimensions $m=6,8,..20$ and neighbors $k=1,3,5,8,10$; we also calculated $k=15$ and $k=17$ for the USD and GBP series respectively, to be consistent with Farmer's recommendation for $k>d+1$. Tables 2-11 present an analytic report of the resulting predictions for all series, including the pre-filtered DM one, summarized as exhibiting low predictability, independently of the embedding dimension or number of nearest neighbors used.

The results are summarized as follows:

USD/GRD

The e error ranged over 1 in nearly all experiments. The best performance was achieved with $k=10$ and $m=18$, which is almost equal to that produced of a simple mean

forecaster. Correlation coefficient results showed an approximately 28% follow-up of the original series, for the same k and m values.

GBP/GRD

All simulations on the British Pound series exhibited worse results than the USD case. The e error proved an inferior predictive performance compared to the mean forecaster, as in all cases it stayed over 1. Correlation coefficient on the other hand resulted a better predictive ability than e , following the jumps of the original series with a rather low value of 28%, which cannot be regarded as a satisfactory forecasting performance. Best performance was observed with $k=5$ and $m=12$.

FF/GRD

The results on the French Franc series show an improved forecasting ability compared to the former two cases, which is justified by a relatively good e error and a mediocre correlation coefficient. The former is slightly better than the simple mean, while the latter indicates a 31% correlation between actual and predicted values. Best results were obtained with $k=8$ and $m=10$.

DM/GRD

Similar predictive behavior was observed for both the returns and the AR(1) pre-filtered returns of the DM series. A relatively good e error compared to the mean forecaster and a correlation coefficient of 30%. The only difference was that the original return series performed best with $k=5$ and $m=16$, while the residuals with $k=8$ and same m .

According to Farmer, we would expect better performance for a number of nearest neighbors above the corresponding correlation dimension. This was confirmed only for the FF and DM series. The fact that these currencies performed better than USD and GBP and behaved consistently with a deterministic explanation, provide for a further

confirmation on the results regarding our systems' structure produced in the previous section.

In order to present a complete analytical framework, we repeated our calculations for the same values of embedding dimension and nearest neighbors as before, but for various library lengths, with more or less similar results. As a last attempt we tried using an augmented or a standard library instead of a rolling one and once again our results remained practically unchanged.

Following the orbit of the reconstructed attractor for each of the four data series we found a number of false nearest neighbours, that is pseudo-neighbours, that belong to another orbit than the one followed by the initial point selected, using the well-known false neighbours test. The number of false neighbours was found to be for USD 273, for GBP 374, for DM 32 and for FF 56. After removing these from each series we repeated our calculations and found that the r coefficient for USD and GBP was just over 0.1, while for DM it outperformed all previous results reaching 0.32. In the case of FF, it stayed at the level of 0.26. The e error was not found to be improved for all currencies involved.

Based on the above results our conclusions lead to rejecting the use of the specific prediction algorithm for these four systems. Predictions made were limited to a success level lower than 35%, which is most unsatisfactory. All series (including the pre-filtered DM/GRD series) exhibited low predictions in every embedding dimension and any neighbor number. Thus, Farmer's algorithm does not seem to be the most suitable

predicting method for experimental data. This was more or less an expected result mostly due to the high level of noise imposed on these systems.

5. Neural Networks Methodology

5.1 Neural Networks

This section is devoted to introducing and analyzing the technique of artificial neural networks which belongs to a class of data driven approaches, as opposed to model driven approaches. Certain general-purpose algorithms address the process of constructing such a machine, based on available data. The problem is then reduced to the computation of the weights of a feedforward network to accomplish a desired input-output mapping and can be viewed as a high dimensional, non-linear system identification problem. In a feedforward network, the units can be partitioned into layers, with links from each unit in the k^{th} layer being directed to each unit in the $(k+1)^{\text{th}}$ layer. Inputs from the environment enter the first layer and outputs from the network are manifested at the last layer. An m - d - 1 architecture, shown in Figure 6, refers to a network with m inputs, d nodes in the hidden layer and one node in the output layer.

We use such m - d - 1 networks to learn and then predict the behavior of our time-series.

The hidden and output layers realize non-linear functions of the form:

$$(1 + \exp(-\sum_{i=1}^m w_i x_i + \Theta))^{-1} \quad (7)$$

where w_i 's denote real valued weights of edges incident on a node, Θ denotes the adjustable threshold for that node and m denotes the number of inputs to a node from

the previous layer. The well known Back Propagation (Rumelhart and McLelland, 1986) we used as a training algorithm.

5.2 System Design

From the given time series $x = \{x(t): 1 \leq t \leq N\}$ we obtain two sets: a training set $x_{\text{train}} = \{x(t): 1 \leq t \leq T\}$, and a test set $x_{\text{test}} = \{x(t): (T+1) \leq t \leq N\}$, where N is the length of the data record. The network is asked to predict the next value in the time sequence, thus we have one output neuron. The number of inputs m is one of the most difficult forecasting investigation aspects and it is examined during the simulations conducted. The problem of the pattern selection strategy for neural networks training, the type of which can be random and deterministic, has been presented comparatively in (Cachin, 1994). Simulation results show that convergence time and learning accuracy can be improved using only deterministic type strategies, which is in fact what we do in our experiments.

5.3 System Implementation, Training and Testing

The system described previously was implemented using a neural network implementation tool, Cortex-Pro Neural Networks Development System (Unistat, 1994). As stated above, the momentum Error Back-Propagation was used to train the networks minimizing the Mean Squared Error, having the learning rate equal to 0.2 and the momentum term equal to 0.9. The initial values of the connection weights were randomly selected in the interval $[-1,1]$ using a uniform distribution. All simulations “run” for 400 iterations during the learning phase (epochs), with the training samples length set to 1200 and the testing ones to 300. Our predicting horizon is one sample value ahead. This is due to the peculiarities present in our systems, mostly because of

the high level of noise imposed, a fact that allows only for short-term forecasting attempts.

The different networks implemented were trained using two transformed data sets, the logarithmic set, used also in Farmer's algorithm, to make possible a direct comparison between the two methods and the raw price data, i.e. the actual (fixed) exchange of the four currencies versus the Greek drachma (Figures 1(a), 2(a), 3(a) and 4(a)). The latter did not undergo a de-trend procedure for two reasons: First because neural networks belong to a class of mapping techniques that do not require such preprocessing and second to investigate whether trend is a significant part of the information needed by a network to generalize. As already mentioned, every data set used as input was first rescaled to the range $[0,1]$ which is required when using the sigmoid function (eq. 7). The number of inputs was chosen to cover from a two days available information to approximately one month (20 samples), after numerous simulations that showed that when the past history fed into the networks was constituted with over one month's daily values the performance was worsen. The number of hidden neurons was also chosen empirically. Because of the heuristic nature of this methodology we conducted our experiments by trial and error, aiming at reaching convergence in time and performance in logical bounds. The reported results were the best achieved.

5.4 Simulation Results

Tables 12 through 15 present those network architectures that performed best according to the NRMSE and Correlation Coefficient error measures when using both the logarithmic and the raw price data sets, for each of our four currency series. The above

errors were measured over the testing (out-of-sample) phase, that is, a set of data excluded from the learning process.

The general conclusion we can derive is that the logarithmic returns exhibit poor predictive behavior for all currencies involved, while untransformed raw prices show a remarkably high and stable level of success. FF and DM produced more successful predictions than USD and GBP, confirming the deterministic nature of their structure. Figures 7 to 10 present graphically the results of the neural network architecture that performed best in each raw price series.

Analytically:

USD/GRD

The return series proved a mediocre forecasting success, with correlation coefficient reaching its highest value at approximately 26% and NRMSE slightly better than the simple mean. The same results were observed when Farmer's algorithm was employed, thus none of the two methods seem to excel. The raw price input on the contrary provided very good results, with almost 98% correlation between actual and predicted series and a very low NRMSE of nearly 0.4 .

GBP/GRD

Identical with the Dollar, the GBP returns resulted a mediocre forecasting success, also similar to the one obtained with Farmer's algorithm, with a slight inferiority regarding the correlation coefficient, which stays below 24%. The same picture is observed regarding raw prices: very high level of correlation, over 98% and a quite low NRMSE of nearly 0.6 .

FF/GRD

Slightly better compared to the previous two cases is the performance of the FF logarithmic series: correlation of 35% and NRMSE lower than the mean forecaster. No significant diversification from Farmer's performance though, which leads to conclude a "draw" for the two methods. Following the stability of raw-price results, the networks achieved high correlation, over 99%, and low NRMSE 0.6 .

DM/GRD

The results reported for the DM series also follow the general setting established by the previous cases: mediocre performance for the returns (both the simple and the AR(1)-residuals), identical to Farmer's NRMSE, but with a slightly lower correlation, and a very successful forecasting behavior for the actual, untransformed prices, that reaches over 99% correlation and 0.6 NRMSE.

6. Evaluation of results

In cases in which the input is in logarithmic form, both methods, that is Farmer's algorithm and neural networks, do not yield satisfactory results being, therefore, not suitable for prediction purposes. The clear superiority of neural networks over Farmer's algorithm as a prediction tool is realised when it comes to using the actual, untransformed rates. The presence of trend, which renders the predictive performance of Farmer's algorithm ineffective, seems to help the networks to embody all the available information regarding the structure of all four currency series and thus produce highly successful results. From an economist's point of view, there should be no preference favouring any particular sort of input type, provided that the prediction obtained is successful. Any explanation, therefore, concerning the preponderance of the raw price data over the first differences of their logarithmic transformations must take place in the context of a rather technical reasoning: Indeed, it appears that the latter, when taken on

a daily basis, yields both positive and negative observations the mean value of which centers around zero, something which does not allow the network to detect and learn a particular pattern of behavior. The raw price data, on the contrary, help the network to learn and generalize more efficiently, especially when it comes to short-term forecasting, since they reveal not only the trend of the rate itself, but possibly, in addition, the short-term expectations of the market. It is reminded at this point that failing to incorporate the complexity of such expectations has been considered as one of the major reasons why satisfactory exchange rate predictions are sometimes difficult to achieve (Pilbeam, 1995).

Turning to the interpretation of the results obtained, these have been, to a considerable extend, anticipated and lead to plausible conclusions as regards the degree of determinism and predictability of the behavior of the drachma exchange-rate fluctuations versus the four currencies involved.

Prediction seems to be more successful in the case of the DM and the FF drachma rates, while that obtained in the case of the GBP and the USD rates appears to be slightly inferior. This difference in forecasting performance is attributed to the nature of the exchange-rate policy followed by the authorities during the period under consideration and which has already been analyzed earlier in this paper. More specifically, targeting the drachma rates with reference to the ECU in which the drachma as well as all other currencies involved in this analysis participate, with the exception of the USD, leads to expecting the corresponding drachma rates against the ECU - participant currencies to be more easily predictable. It has been argued in the literature, in fact, that ECU participation seems to be an asset in exchange-rate prediction (Six, 1989), particularly

in cases like the rates of the DM and the FF which represent more than 50% of the total ECU participation. In addition, the hard-drachma policy used as an anti-inflationary device, provided for very low fluctuations for the rates of these three currencies versus the Greek drachma, something which adds an element of discipline in the behavior of these series, thus making their future course more predictable.

The increased predictability thanks to these low exchange-rate fluctuations has been reinforced, particularly for the DM and the FF rates by their ERM participation for the period under review. The bands within which the rates of the two currencies have been allowed to fluctuate in the international markets contributed to their disciplined behavior and, consequently, to the increased predictability associated with it.

The case of the GBP results seems to reinforce our line of argument: The GBP has always been an ECU participant, whereas its ERM membership has been suspended on the 16th of September, 1992. Predictions associated with the drachma rates versus the GBP, therefore, are expected to be inferior compared to the DM and FF rates for the same sample period, to the extent that its short ERM membership may count. Indeed the prediction results obtained on the basis of the algorithms employed are very much in accordance with the line of argument stated above.

Irrespective of the prediction performance regarding the drachma rates versus the various currencies involved in this paper, one must point out that all four time series are expected to be noise-polluted due to exogenous disturbances of two categories: Those resulting from corrective measures taken by the authorities in order to offset possible undesired exchange rate developments and those resulting from certain irregular factors,

not necessarily of economic nature. Typical cases of the latter include the 1987 stock market collapse, the German political and economic reunification in 1990 and the ERM wider bands in 1993. Similar factors introducing noise on the drachma side may be taken to be the 1985 devaluation, the prolonged pre-election period between 1989 and 1990 and the complete liberalization of capital movements in 1994.

It becomes obvious, therefore, that time series composed of empirical observations like daily exchange rates are difficult to interpret and forecast and that minimizing the presence of noise in such cases is a tedious task. The main problem arises because, as earlier stated, these rates are to a significant extent affected by the interference of the authorities in the framework of a predetermined exchange-rate policy. It has already been pointed out in the introduction of this paper that Taylor (1995), in a comprehensive survey on the issue of exchange rates, indicates the existence of evidence concerning a link between official intervention and exchange-rate predictability. What remains to be seen in this paper is the sort of link that exists when it comes to the specific case of the Greek drachma versus the four currencies involved and the extent to which the impact of the authorities' interference is favorable or adverse. An additional complication is introduced due to the choice of the particular sample period, in the course of which both the logic and the extent of the government intervention vary considerably. Thus, the beginning of the period under consideration is characterized by generous depreciation rates, including a drachma devaluation, while the beginning of the 90's introduces the "non-accommodating" exchange-rate policy.

These complications suggest that future research should be undertaking focusing on the rates of the major currencies as these are determined in the international markets and in

the case of which the presence of noise is expected to be weaker. Once a successful forecast for such rates has been realized, these rates may be used to derive drachma cross-rates, on the basis of a preannounced government policy. This tactical move is expected to avoid a considerable degree of noise and yield more reliable results.

7. Conclusions

This paper has focused on examining the degree of predictability of the Greek drachma exchange rates with respect to four major currencies, using methods and techniques of non-linear dynamics and neural networks and has resulted to the following main conclusions:

1. The FF/GRD and DM/GRD time series exhibit chaotic behavior, with attractor dimensions of approximately 8 and 6 respectively, while the USD/GRD and GBP/GRD time series exhibit a more random behavior. Given these chaotic characteristics, Farmer's algorithm has been applied to test the prediction of all four series involved, plus that of the pre-filtered DM/GRD. This exercise resulted in indicating that all time series exhibit low predictions in every embedding dimension and any neighbour number, with the level of the performed predictions being as low as about 30%, which is obviously not satisfactory. Thus Farmer's algorithm does not seem to be the most suitable predicting method, for such experimental data, with high level of noise.

2. Simulations in the context of neural network methodology involving first differences of logarithmic values were equally unsatisfactory to those obtained using Farmer's algorithm. On the contrary, positive and highly accurate simulation results have been

derived using as input the actual, untransformed exchange-rate figures. The networks have been very successful in learning all exchange-rate series involved and thereby in making accurate predictions.

3. The nature of the Greek economic policy which involves the determination of drachma rates with reference to the ECU in which the DM, the FF and the GBP occupy an overwhelmingly large percentage of the total currency participation, contributes to the predictability of the exchange rates of these currencies versus the drachma. The USD/GRD rates, on the contrary, seem to be tougher to predict, due to the absence of any such link between the two currencies in terms of economic policy planning.

4. An additional element of discipline that concerns particularly the DM and the FF and, to a much lesser extent, the GBP is related to the ERM membership of these currencies. Indeed, restricting the fluctuations of these currencies in the international markets within the ERM bands provides for increased discipline in the behavior of their exchange-rates. This element of discipline adds to the predictability of the rates of these currencies versus the drachma due to the reason analyzed in point 3 above.

5. A final point concerning the conclusions of this paper relates to the contribution of government interference in the drachma rates prediction. More specifically, targeting the exchange-rate policy with reference to the ECU in which the DM, the FF and the GBP participate, the former two being, in addition, full ERM members for the period under review, adds to the predictability of the exchange-rates of these currencies versus the drachma. It seems, therefore, that, in what concerns drachma exchange rates against these currencies, the effectiveness of official intervention regarding the predictability of

these rates is not as unclear as it has been claimed in the literature.

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LEGENDS FOR FIGURES

Figure 1: USD/GRD time series plots: (a) Daily fixed-rates, (b) Daily returns

Figure 2: GBP/GRD time series plots: (a) Daily fixed-rates, (b) Daily returns

Figure 3: DM/GRD time series plots: (a) Daily fixed-rates, (b) Daily returns

Figure 4: FF/GRD time series plots: (a) Daily fixed-rates, (b) Daily returns

Figure 5: Correlation dimension estimates versus embedding dimension for the USD/GRD, USD/GRD, DM/GRD and FF/GRD series of returns.

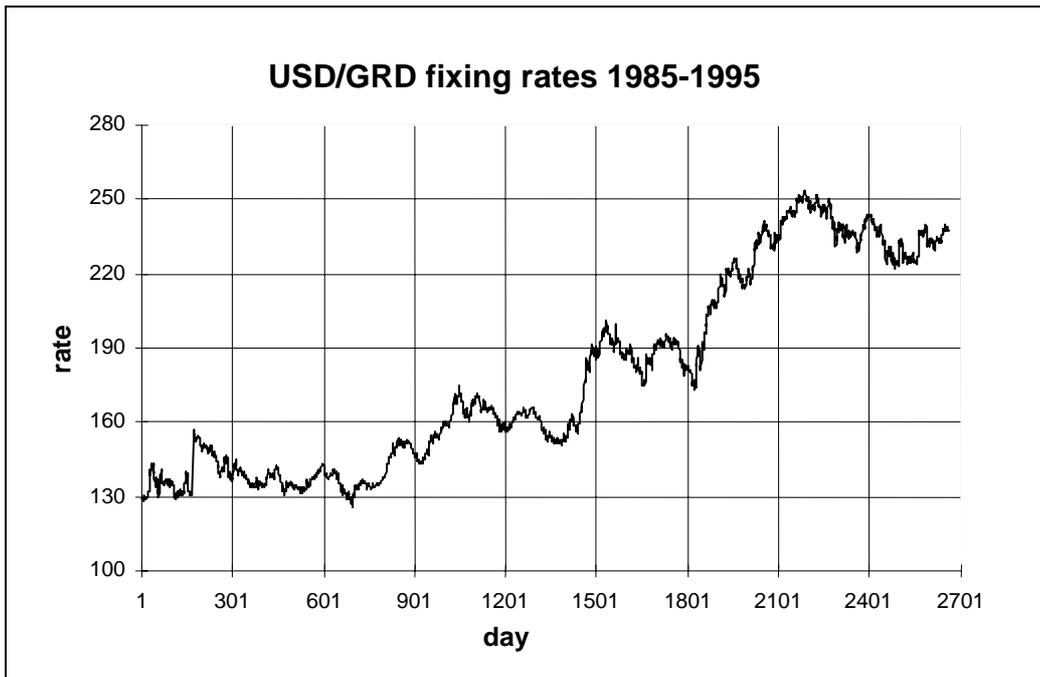
Figure 6: The m-input, d-hidden nodes and 1-output MLP neural network architecture.

Figure 7: Actual values versus neural network predictions of the USD/GRD fixed rates series using a 6-5-1 MLP architecture.

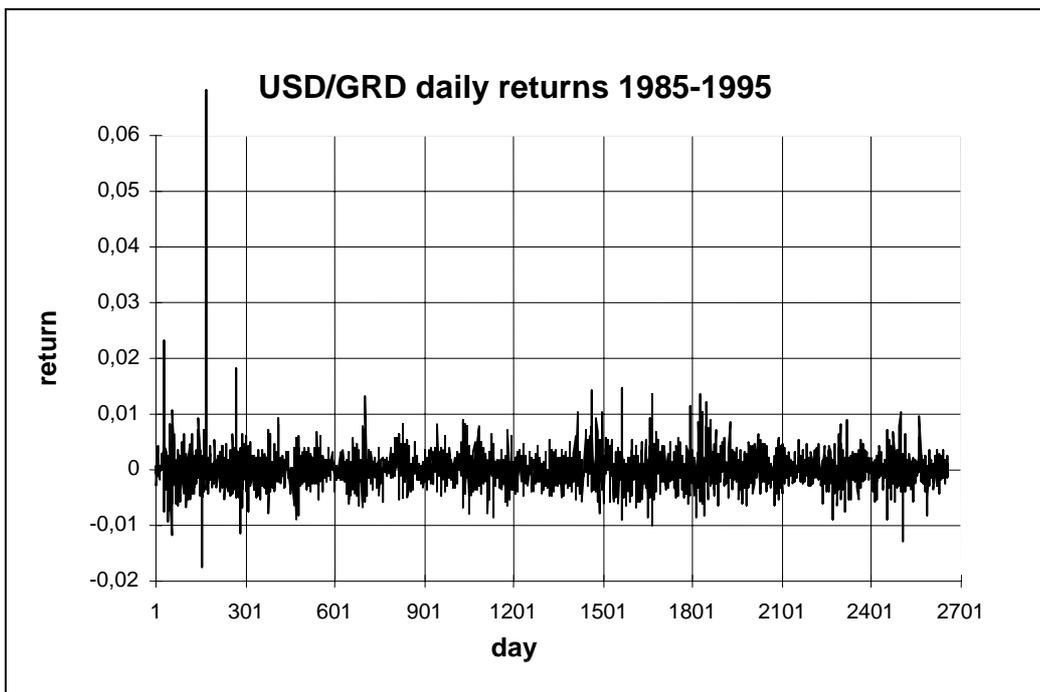
Figure 8: Actual values versus neural network predictions of the GBP/GRD fixed rates series using a 2-5-1 MLP architecture.

Figure 9: Actual values versus neural network predictions of the FF/GRD fixed rates series using a 2-3-1 MLP architecture.

Figure 10: Actual values versus neural network predictions of the DM/GRD fixed rates series using a 2-5-1 MLP architecture.

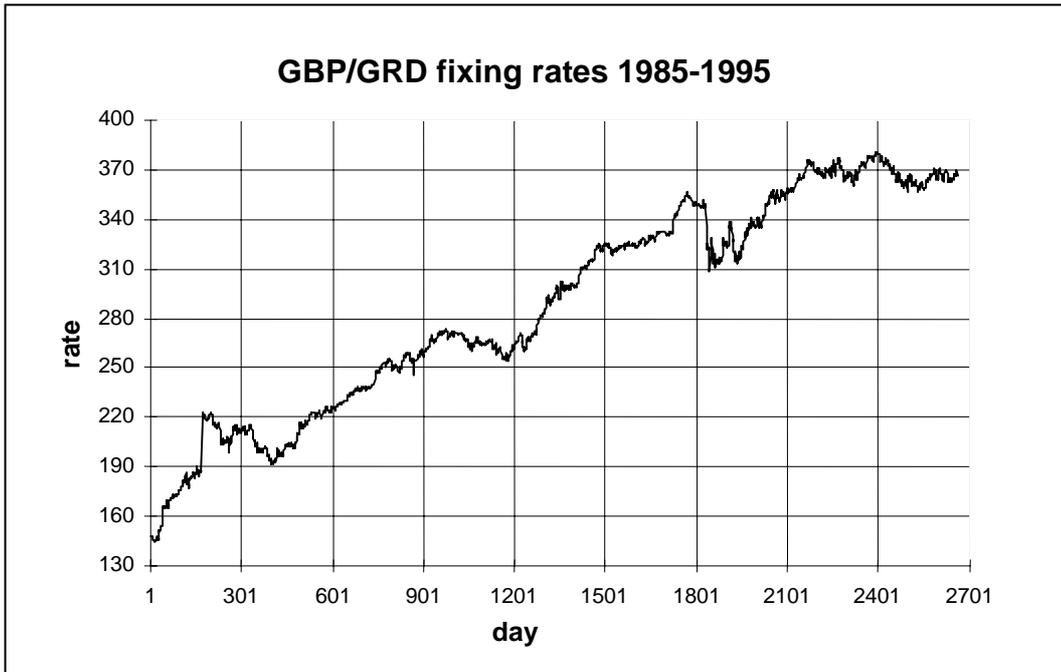


(a)

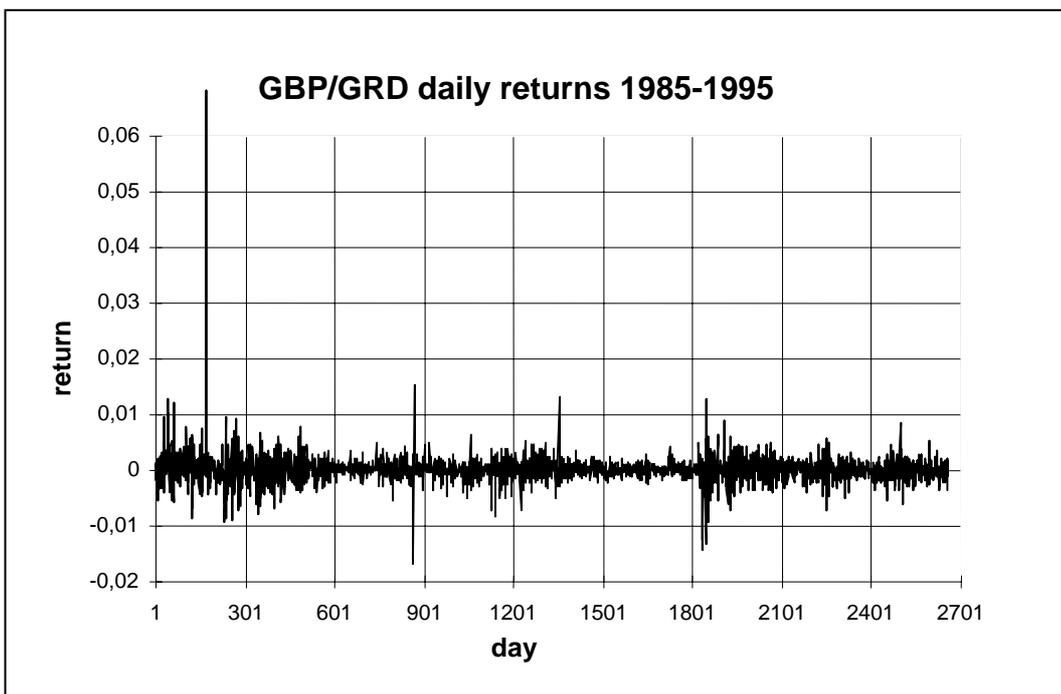


(b)

Figure 1

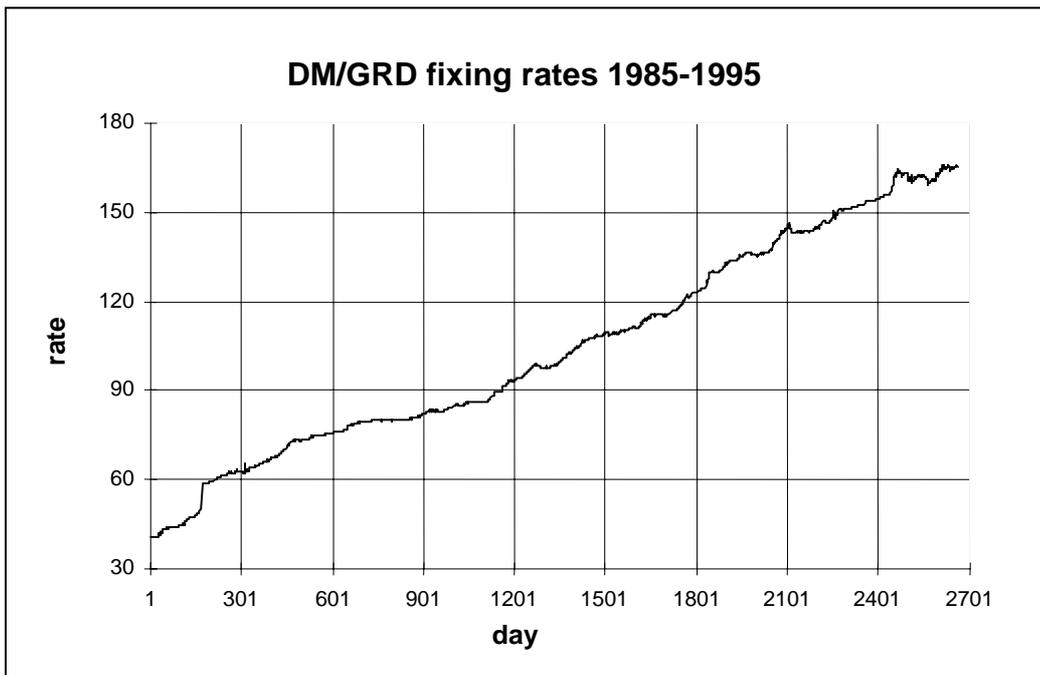


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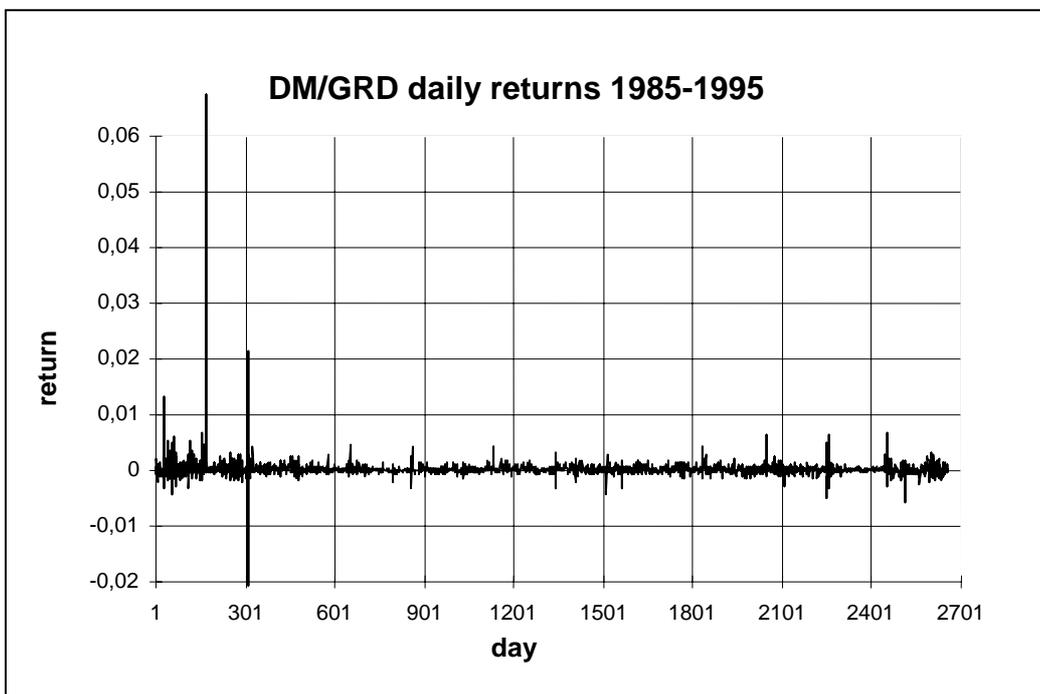


(b)

Figure 2

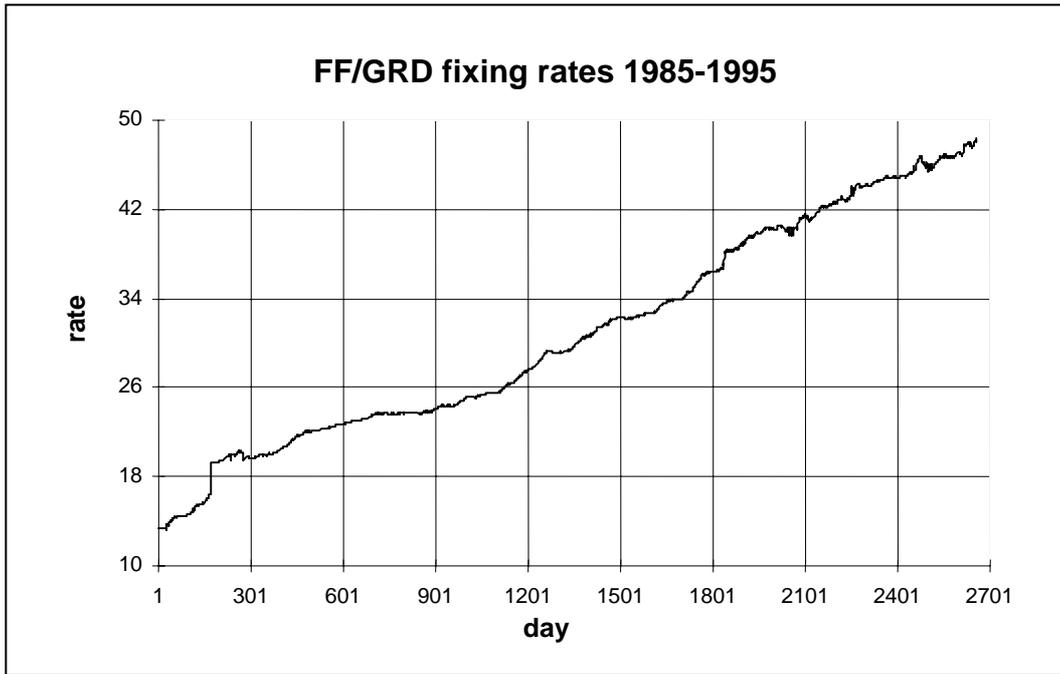


(a)

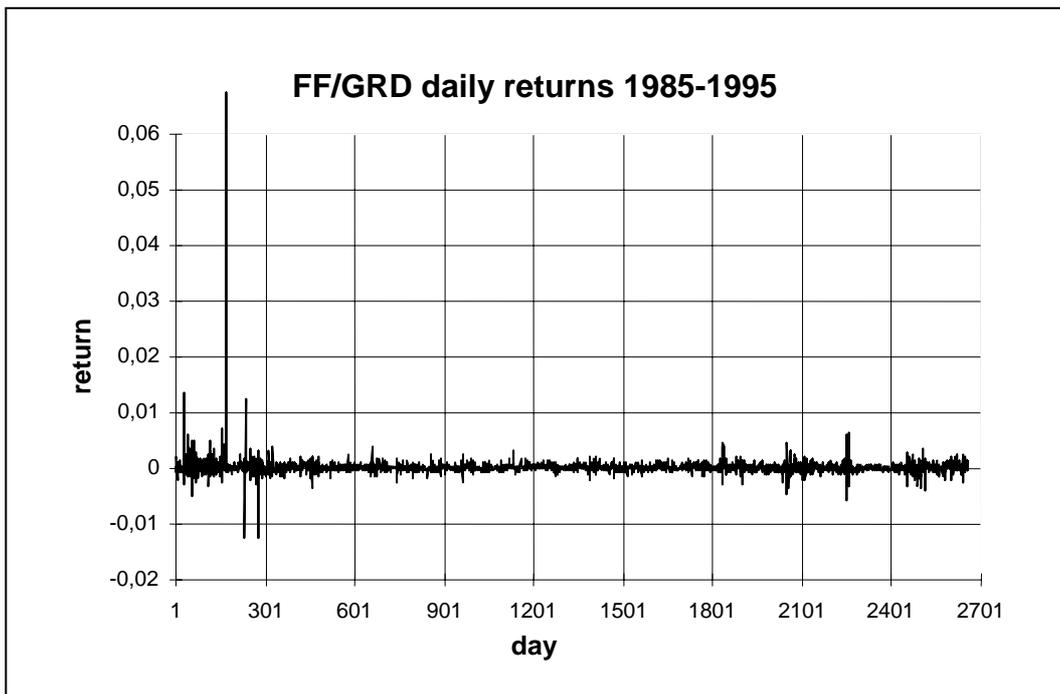


(b)

Figure 3



(a)



(b)

Figure 4

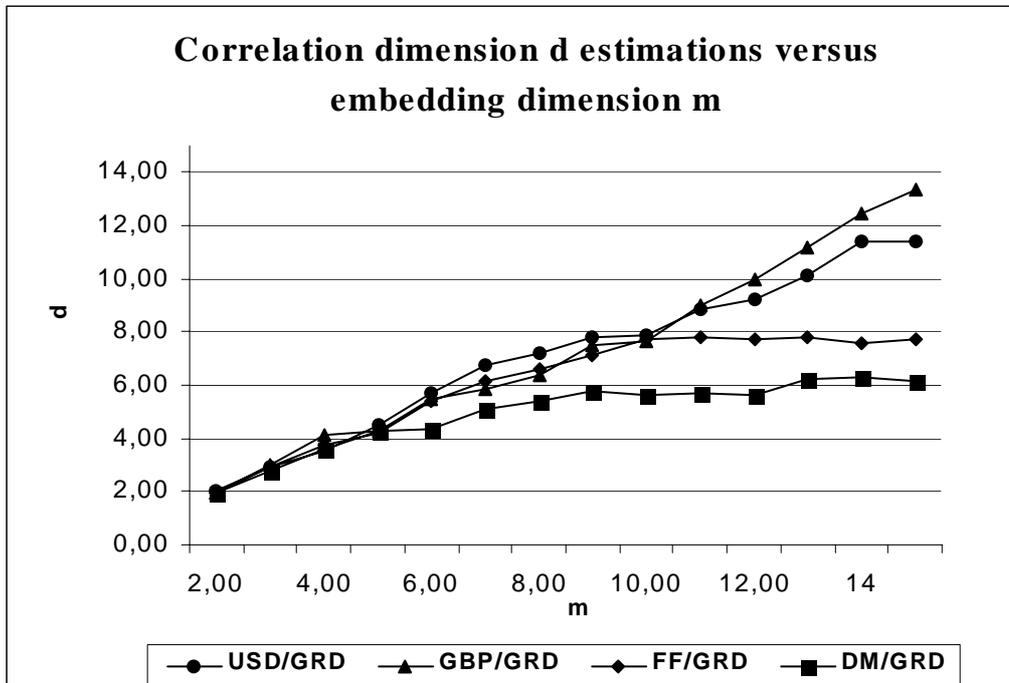


Figure 5

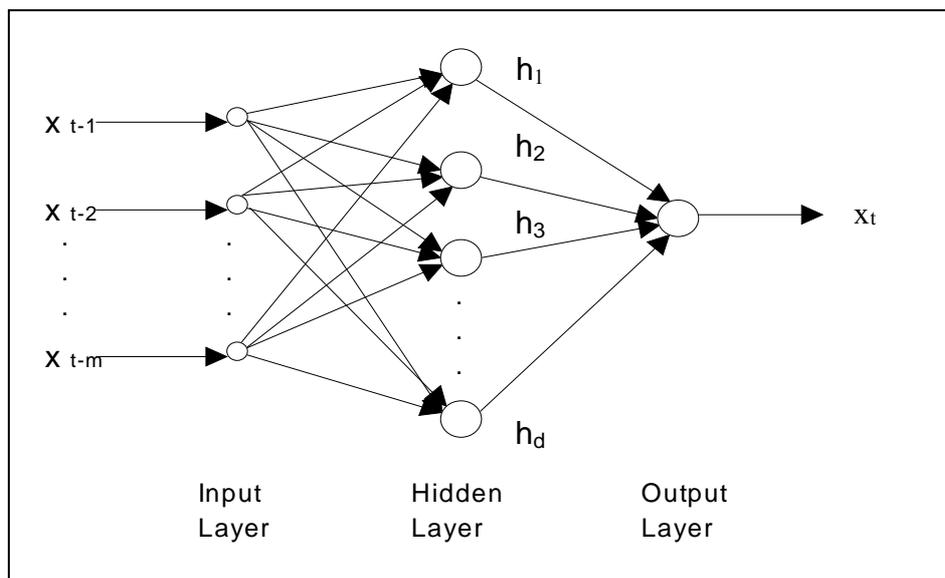


Figure 6

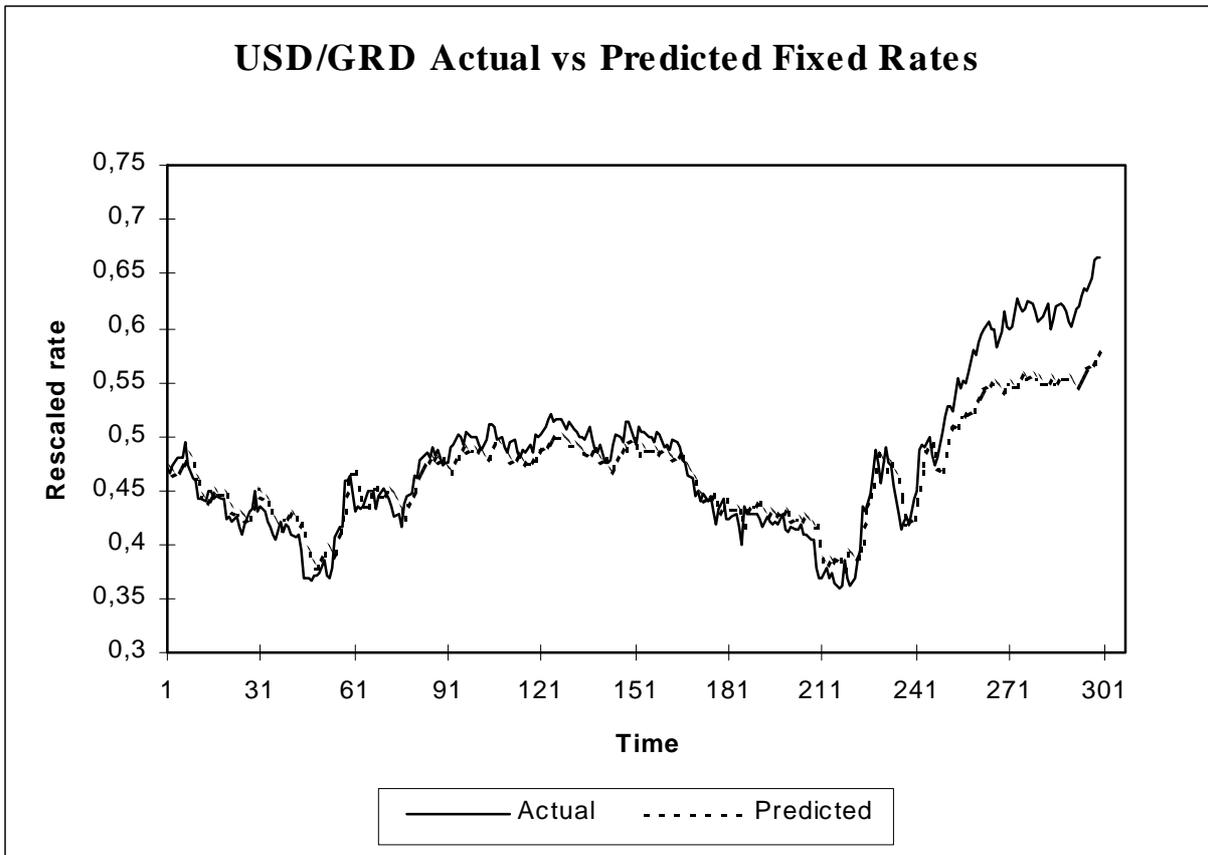


Figure 7

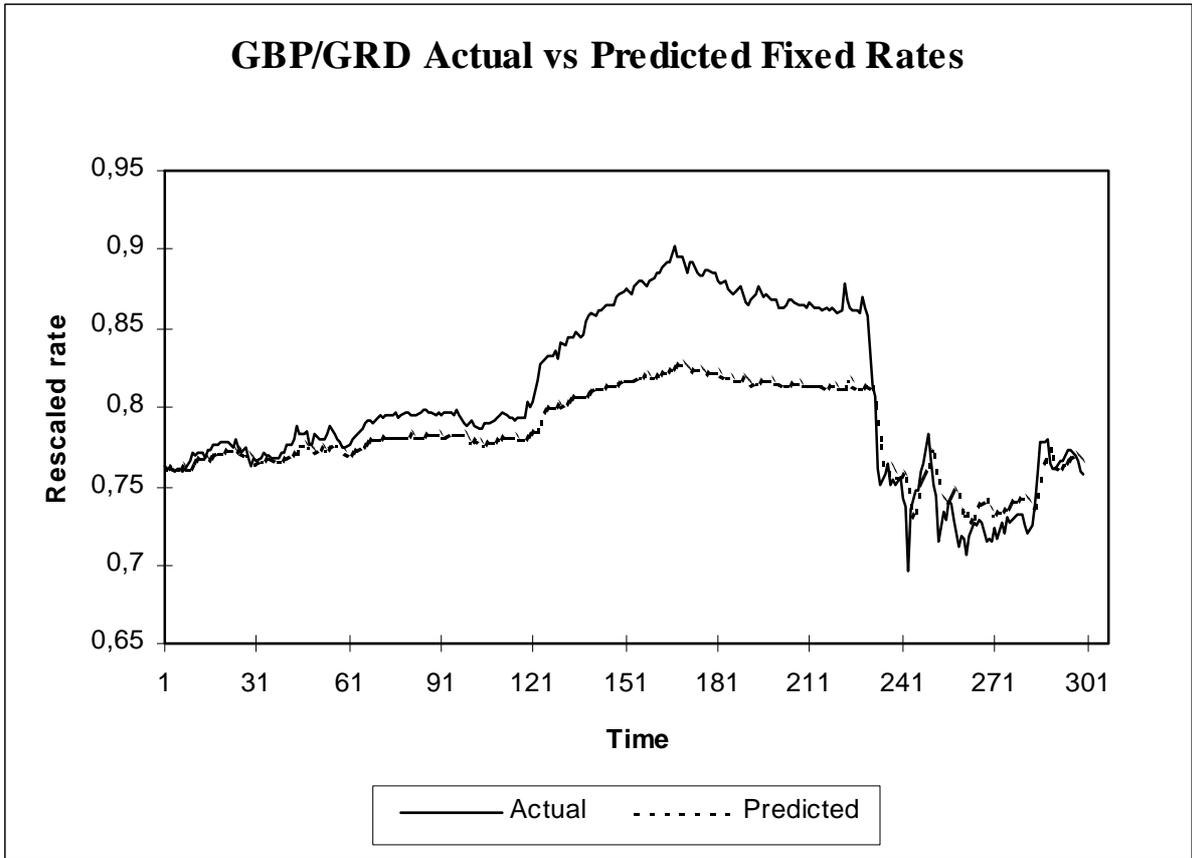


Figure 8

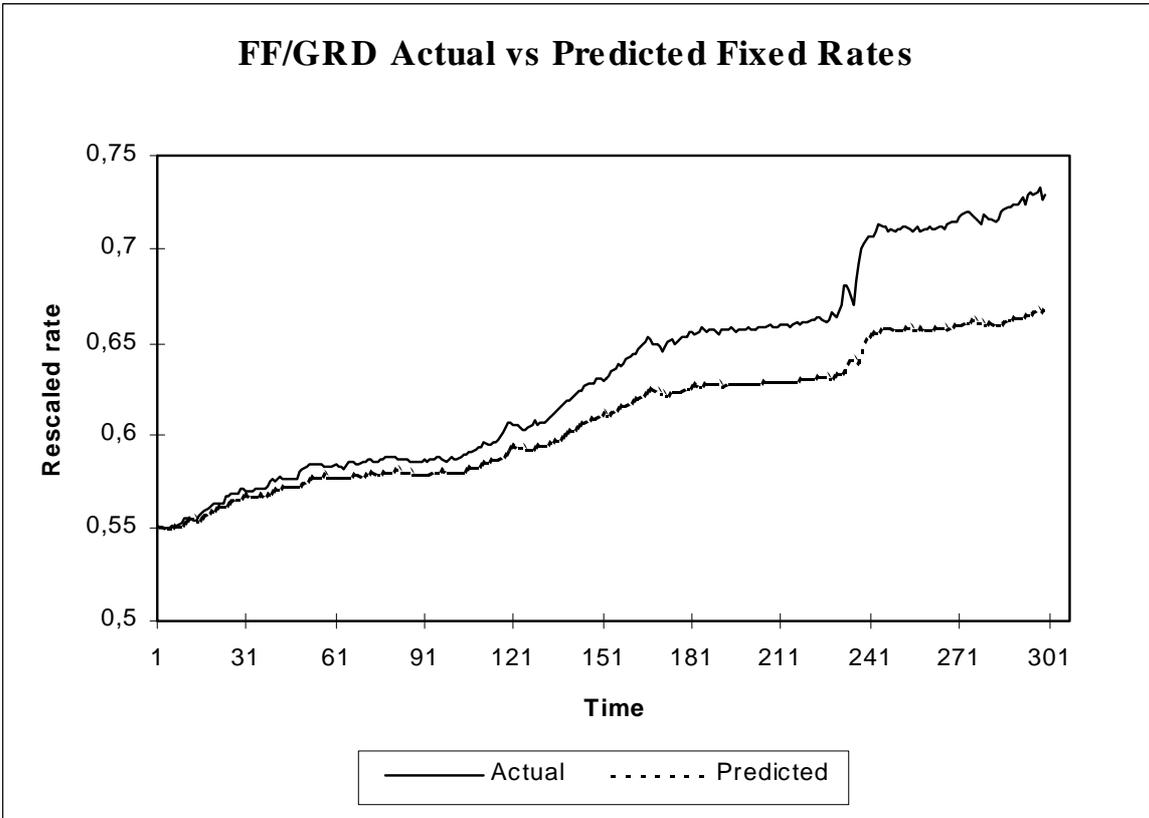


Figure 9

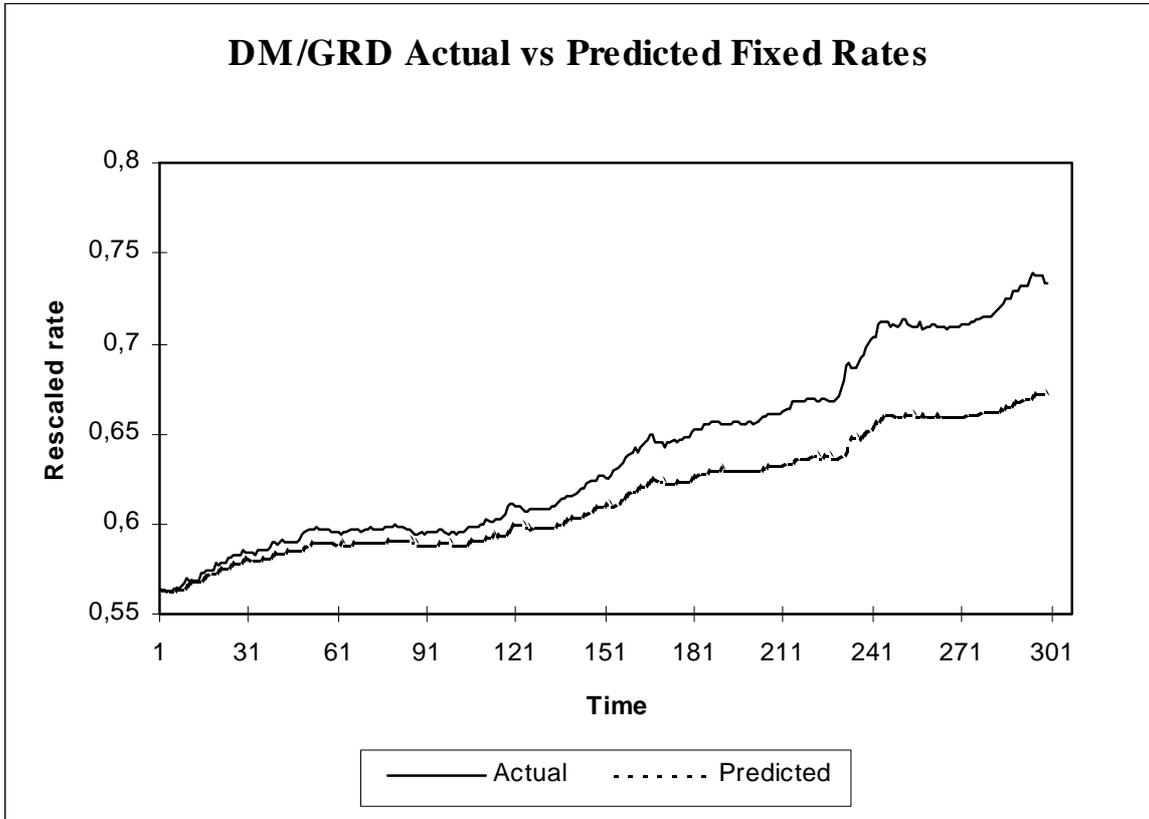


Figure 10